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Estimating Emissions Impacts to the Bulk Power System of Increased Electric Vehicle and Renewable Energy Usage

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Estimating Emissions Impacts to the Bulk Power System of Increased Electric Vehicle and Renewable Energy Usage

by

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Abstract

The research presented in this thesis examines the use of electric vehicles and renewable energy to reduce emissions of CO_2, SO_2 and NO_x, and within the state of Texas. The analysis examines the impact of increased renewable energy output and electric vehicle charging on the emissions of fossil fuel electric generators used to serve the bulk power system within Texas. The analysis then compares those impacts to alternative scenarios in which fossil fuel generation replaces some renewable energy generation, and Internal Combustion Engine (ICE) vehicles of varying efficiency are used instead of electric vehicles.

This research uses temporally-resolved regression analysis combined with a unit commitment and dispatch model that incorporates several different scenarios for EV charging and fuel mixes to evaluate emissions outcomes based on a variety of conditions. Hourly historical generation and emission data for each fossil fuel generator, combined

with hourly output data for non-fossil fuel units aggregated by fuel type (i.e. nuclear, wind, hydro-electric) within the Electric Reliability Council of Texas (ERCOT) footprint is regressed to assess the impact of wind generation output on fossil-fuel generation emissions. The regression analysis is used to assess potential increases in emissions resulting from the ramping of fossil-fuel Electric Generation Units (EGUs) to compensate for variability in wind generation output due to changing weather conditions.

The unit commitment dispatch model is used to evaluate the impact of changes in customer demand due to increased usage and charging of electric vehicles on the ERCOT system and any resulting increase in emissions from generation used to meet this new demand. The model uses detailed cost, performance and emissions data for EGUs in the ERCOT footprint to simulate the impact of a variety of charging scenarios and fuel mixes on EGU dispatch patterns and any resulting change in system-wide emissions. The results of this model are combined with the results of the regression analysis to present a more complete analysis of the combined impacts of increase EV and renewable energy usage on the emissions of CO_2, SO_2 and NO_x within the ERCOT footprint.

Based on these analyses the increases in renewable energy generation demonstrate clear benefits in terms of emission reductions when the impacts of increased emissions due to more frequent ramping of fossil-fuel units are taken into account. This analysis also finds that EV charging generally has emissions benefits across a range of charging patterns and bulk power system fuel mixes, although in certain circumstances EV charging might result in higher emissions than the use of ICE vehicles. This research finds when future ICE vehicles with reduced emissions are taken into account, approximately half of the modeled scenarios show net emissions benefits from EV charging, while half show net emissions costs when emissions impacts across pollutants are taken into account.

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1) Introduction: Motivation and Scope

Electric vehicles have been promoted by policymakers as a way to reduce fossil fuel usage in the transportation sector, which in total accounts for almost 30% of total U.S. emissions of CO_2 (EPA, 2013g). The emissions impact from electric vehicles is largely dependent on three factors: the emissions profile of the electric generation used to charge the electric vehicle's storage system, the efficiency of a conventional Internal Combustion Engine vehicle (ICE) that would have been driven instead of the electric vehicle, and the carbon intensity of the fuel used in the ICE. This research develops a detailed methodology for evaluating the emissions tradeoff between an EV and an ICE to better understand the environmental impacts of greater EV adoption as well as a variety of electric generation and EV charging pattern scenarios in 2025.

In addition to EVs, renewable energy has been offered in many situations as a policy alternative to reducing Greenhouse Gas (GHG) emissions through direct regulation of emissions –primarily CO_2 – and other pollutants in the U.S. without the need for direct GHG regulation. The use of renewable energy to provide electricity to end-users might offset the use of fossil-fuel generation, thereby reducing GHG emissions as well as emissions of SO_2, NO_x and other pollutants. At the same time, generation from variable renewable EGUs such as wind power and solar power might cause inefficiencies in fossil-fueled EGUs commonly used to "even out" renewable energy output; coal fired boilers and their pollution equipment might in particular lack the flexibility to ramp up and down quickly. As a result, it has been hypothesized that when such facilities are ramped up and down, the amount of fuel burned per unit of electricity produced -- and the associated emissions -- increases dramatically. The resulting efficiency loss is incorporated in the research to more completely assess the impact of renewable energy in reducing CO_2, SO_2, and NO_x emissions.

Using a combined analysis of EV emission tradeoffs and any fossil-fuel EGU efficiency loss associated with increased renewable energy generation, this research models three bulk power system "scenarios," which simulate current and potential future fuel mixes and electric demand patterns. This analysis simulates several EV charging sensitivities based on a variety of simulated charging patterns for two electric vehicles, the Nissan Leaf and the Chevy Volt; the development and characteristics of scenarios and sensitivities are discussed in more detail in Chapter 2. This analytical approach finds that EV usage generally reduces the combined societal cost of emissions of CO_2, SO_2 and NO_x assuming today's light-duty vehicle fleet average efficiency of 30 mpg on conventional blends of 90% gasoline and 10% ethanol. Under 7 out of 15 charging sensitivities, reductions are also found even when emissions associated with EVs are compared to the 2025 Corporate Average Fuel Economy (CAFE) standard of 54.5 mpg, which is much more efficient than today's average fleet efficiency. However it is estimated that the 54.5 mpg CAFE standard might only be equivalent to 36 mpg as estimated by the EPA (Edmunds, 2013).[1] Meaningful differences are also found in the emissions impact of different EV charging strategies assuming current generation fleet fuel mix. These differences in charging strategy outcomes are reduced if "leveled" daily

[1] "CAFE results and accounting practices never changed to match the [EPA] window-sticker mpg figures, however. CAFE mpg still comes from the original pair of tests that are now widely viewed as bad predictors of real-world mpg. The 34.1 mpg CAFE target for 2016 is actually equal to only 26 mpg on a window sticker. The talked-about 2025 CAFE standard — usually described as 54.5 mpg — amounts to a figure of 36 mpg Combined on a window sticker." (Edmunds, 2013)

loadshapes are assumed as a result of potential growth in demand response and energy storage.

1.1) Motivation for the reduction of emissions associated with fossil fuel use

According to the Intergovernmental Panel on Climate Change (IPCC) "It is *extremely likely* that human influence has been the dominant cause of the observed warming since the mid-20th century… Continued emissions of greenhouse gases will cause further warming and changes in all components of the climate system. Limiting climate change will require substantial and sustained reductions of greenhouse gas emissions." (emphasis in original) (IPCC, 2013). While there are a number of greenhouse gasses that contribute to this impact, the IPCC identifies global emissions of CO_2 as the "most important" anthropogenic GHG in their 2007 Synthesis Summary Report for Policymakers. The report identifies a wide variety of potential impacts to human health, society and industry throughout the planet and the potential scale of these impacts has made reduction of GHG emissions a national and international priority.

The reduction of SO_2 and NO_x has been identified as a national priority and are expected to result in health, environmental and economic benefits; recent analyses have attempted to quantify the impacts of these emissions, finding substantial value in their reduction (Epstien et al., 2011). Emissions of SO_2 and NO_x have long been associated with negative impacts to human health and the broader ecosystem, and the EPA has regulated the emission of both pollutants since 1971 (EPA, 2013g), (EPA, 2013h). Since 1971 reduction in emissions of these pollutants has been achieved through a variety of regulatory mechanisms, and the increased use of EVs and renewable energy may reduce the burden of emissions regulations on industry. To the extent that the use of renewable energy and EVs are subsidized, the impact of those subsidies must be accounted for, however such an accounting is beyond the scope of this thesis.

1.2) Motivation for transportation electrification

The electrification of the transportation has been cited by policymakers as an important long term objective in the effort to reduce emissions of CO_2 and thus mitigate the impacts of climate change. A comprehensive report on climate change mitigation strategies to address California's goal of reducing GHG emissions by 80% below the 1990 emissions level by 2050 was released in 2012 and identified the electrification of most direct fuel use as one of three key components necessary to achieve California's policy goal (James H. Williams, 2012). While the report is focused on the reduction of emissions in California, which has different vehicle usage and EGU fuel mix patterns, analyses have identified vehicle electrification as an important component of reducing GHG emissions (Thomas, 2009). According to the most recent EPA analysis, the transportation sector accounts for 28% of GHG emissions in the U.S., the second largest identified source behind the generation of electricity (EPA, 2013f).

In his report, Williams found that "there was no alternative to widespread switching of direct fuel uses (e.g., gasoline in cars) to electricity in order to achieve the reduction target." Further, the report identifies the transportation fleet as providing the greatest share of GHG reductions from electrification. It is important to note that these savings include the effects from a presumed decarbonization of electric generation, also identified as a necessary component to achieve the state's 80% reduction goal.

Electric vehicles may help achieve other important policy goals, including environmental, economic and security objectives. Additional environmental impacts from the expanded use of electric vehicles may be substantial, such as potential reduction of ground level ozone and SO_2 emissions both of which pose significant health risks to the public. A 2009 study found that EVs can provide substantial health cost savings when charged using non-polluting electric resources; the study evaluates the benefits of EVs assuming a certain penetration level by 2030 and finds that the Net Present Value of health cost savings ranges from $105 to $210 billion (Thomas A. Becker, 2009).

Expanded domestic automotive manufacturing has also been cited as a motive for policy support for EVs. Indeed, several leading EVs including the Chevy Volt, Nissan Leaf, and Tesla Model S (Voelcker, 2013) are manufactured domestically, although the relationship between the nature of the vehicle and the need for domestic production is unclear. Finally "energy security" or dependence on imported petroleum has often been cited as a key policy rationale to move toward electrification of the U.S. transportation fleet. In Becker et al., the authors find that U.S. oil imports are 18%-38% lower in 2030 than would otherwise be the case, reducing the trade deficit by $94-$266 billion in 2030.

1.3) Motivation for Renewable Electricity Generation

The use of renewable energy has been offered by policy makers as both a policy alternative to reducing Greenhouse Gas (GHG) emissions through direct regulation of emissions, and as a useful mechanism to leverage the benefits of electric vehicles in mitigating GHG emissions from the transportation (Lutsey, 2008). In many states this effort to promote renewable energy as an alternative or in addition to GHG regulation has taken the form of a Renewable Portfolio Standard (RPS), with variations from state-to-state for the extent and nature of the requirements. However, concerns have been raised regarding the efficacy of an RPS, and renewable energy in general, in reducing CO_2 emissions (BENTEK, 2010). Furthermore, it has been suggested that renewable power actually causes increases in emissions of other pollutants (BENTEK, 2010) and (Katzenstein & Apt, 2009).

Emissions from the bulk generation of electricity are determined primarily by the amount and type of fossil fuels such as coal, oil, and natural gas used to generate electricity. The use of renewable electric generation in most cases is assumed to offset the use of fossil fuel generation thereby reducing emissions associated with fossil-fueled electric generation. As a result, policymakers often identify renewable electric generation as a key component of any strategy to reduce CO_2 emissions. In the U.S., the bulk power sector accounts for 33% of GHG emissions, the largest single portion among identified sources (EPA, 2013f).

Additionally, the relative GHG impact of EVs relies primarily on the mix of electric generation used to supply vehicles with electricity; however the emissions associated with electric generation, specifically intermittent renewable energy requires additional analysis as well. It has been hypothesized that renewable generation such as wind and solar can result in increased emissions of pollutants across a system despite the low emissions of the wind turbines and solar panels themselves. This is because the variable nature of wind and solar requires a firming resource to compensate, often fossil-fueled electric generation units (EGUs) which must then frequently ramp up and down.

Pollutant controls used to reduce emissions from fossil-fueled EGUs also affect the impact of variable renewable generation as they are ramped up and down, in some cases independently of EGU output ramping, rather than operating at steady-state conditions. This ramping nature can cause inefficiencies in fossil-fueled EGUs, raising their per-unit fuel consumption and emissions, because some generation technologies and their emissions control equipment might lack the flexibility to ramp up and down quickly. It is the potential for efficiency losses by thermal generator induced by variable power sources from renewables that most often calls into question the benefit of renewable energy in reducing emissions. For the purposes of this paper this efficiency loss and any resulting emissions impacts is called the "secondary effect" of wind EGU output on emissions.

Researchers at Carnegie Mellon University, including Dr. Jay Apt and Dr. Warren Katzenstein have studied this problem through the application of a theoretical model based on select natural gas generator characteristics, but did not incorporate changes in overall demand. Dr. Joseph Cullen has examined this question as well but did not use time-resolved historical data to establish correlations or causality between wind and emissions rates, focusing instead on identifying specific power plants commonly offset by wind. A recent analysis by the National Renewable Energy Laboratory uses a unit commitment and dispatch model similar to that used in the EV modeling scenarios to assess the impact of increased wind and solar generation in the Western U.S on fossil fuel emissions due to increased reamping (NREL, 2013).

This paper seeks to answer similar questions through an examination of detailed historical emissions and heat rates of power plants over time. Using the EPA's Clean Air Markets Emissions Database for all reporting EGUs (EPA, 2013b), hourly data for fossil fuel EGUs within the ERCOT electric grid in Texas were analyzed with the intent of determining whether increased wind generation impacted emissions from these power plants. Additional data from ERCOT with EGU hourly output by fuel type was also analyzed for this research.

This analysis examines the relationship between increased levels of wind energy generation and emissions per unit of electricity produced using historical data for electricity output and CO_2, SO_2 and NO_x emissions in the Electric Reliability Council of Texas (ERCOT). The results from this analysis inform the research in this paper by providing a useful estimate of the "secondary impact" of increased renewable energy use that is incorporated with the results of the unit-commitment dispatch model to estimate the combined impact to emissions of increased renewable energy and EV usage.

The marginal changes in emissions intensity depends on operational levels, marginal heat rates, and other technical factors, as a result the effect of ramping on EGU emissions is non-obvious. However, it is hypothesized by this work that those rates are non-linear and difficult to predict. Thus, the research in this paper seeks to use historical performance data to develop a quantitative model of causal relationships between wind energy variability, system variability, and emission rates.

In addition to developing a more sophisticated model, the analysis for the work presented here uses a more detailed set of data to examine the influence of the intra-hourly change in wind energy output on system-wide emissions. The analysis in Meehan (2012) relied on a dataset of hourly interval power plant output provided by ERCOT, along with an hourly interval emissions dataset from the Environmental Protection Agency (EPA). Limiting this analysis to ERCOT provides similar advantages to those discussed earlier in this thesis and is consistent with an overall approach of evaluating emissions impacts in the context of an isolated market.

1.4) Bulk Power Sector Modeling

The research in this thesis uses two primary analytical approaches to model impacts to the bulk electric generation sector: temporally-resolved regression analysis and a commercially available unit commitment and dispatch model. Both approaches use publicly available detailed data to model EGU specific performance characteristics and emissions; the regression analysis uses historical EGU performance characteristics to estimate emissions associated with fossil fuel EGU ramping to accommodate wind EGU variability; the unit commitment and dispatch model uses current EGU characteristics and assumed characteristics of future EGUs to model a variety of EV charging and renewable electricity generation scenarios.

The use of bulk power sector modeling provides the ability to understand the impacts of hypothetical changes to the bulk power system based on a variety of assumptions. The goal of this research is to assess the impact on electric and transportation sector emissions of a variety of hypothetical future scenarios. As a result, it is necessary to model the bulk power system based on current characteristics, developing a set of scenarios and sensitivities based on variations in the hypothetical future scenarios.

1.5) The Context of using Texas as a Testbed

Texas serves as a valuable testbed for this analysis as a result of several policy decisions that have led to a market that has extremely limited capabilities to import or export energy to other markets, as well as the development of substantial amounts of wind energy generation. The isolated nature of ERCOT's market is largely a result of a long-standing policy among electric providers to avoid federal regulation by ensuring that providers serving Texas customers generated and sold electricity within state borders. Policy decisions that have driven wind energy development include the deregulation of the wholesale electric generation market, the establishment of a statewide goal for renewable energy production, favorable transmission rules that socialize the cost of power plant interconnection, and the creation of a robust transmission infrastructure to serve regions of the state with high renewable energy potential. As of 2012 wind energy accounted for 13% of electric generation capacity in ERCOT and 9.2% of total generation for the year (ERCOT, 2013), much of which is anti-correlated to load but under certain policy scenarios could be well correlated with EV charging times.

The lack of synchronous interconnections with other regional transmission organizations results in a level of isolation that is helpful in determining the impacts of changes in the region's generation energy portfolio that would not be possible in a state or electric grid that is part of one of the two other interconnections covering the rest of the continental U.S. (the Eastern Interconnect and the Western Electricity Coordinating Council). In contrast with the other interconnections, which are impacted by the policies from multiple states, ERCOT represents a unique case study because only a single RPS policy is relevant for Texas, the key policy context was established in 1999, when Senate Bill 7 was passed by the Texas State Legislature to restructure the electric market and establish a goal for the state to achieve 2,000 MW of new renewable energy generating capacity by 2015.

In contrast with other states, whose RPS regulations typically set requirements for an amount of energy produced (in MWh), the Texas RPS set a standard for capacity (in MW) without specifying the level or type (such as peaking) of output required of installed capacity. This unique approach was favorable for wind, whose low capacity cost was appealing despite its intermittent nature. The 2,000 MW goal was on track to be met many years ahead of schedule, and in 2005 the RPS standard was set at a higher level of 10,000 MW by 2025. As a result of this policy mechanism, along with market conditions and federal Production Tax Credits, ERCOT now has over 10,000 MW of installed wind power. The history of wind development in Texas combined with the isolated nature of ERCOT provides this analysis with a convenient data source to examine correlations between wind output and fossil-fueled EGU combustion emissions. Texas also exhibits strong seasonal and daily changes in demand patterns due to high air conditioning loads in the summer with seasonal changes in peak demand exceeding 35,000 MW and daily changes in demand exceeding 28,000 MW (Wattles, 2012). These rapid and large changes in demand make the region interesting to analyze relative to more temperate regions with moderate seasonal and daily changes in demand from the perspective of assessing how new demands on the system impact those rapid changes.

Many states and regions have pursued policies similar to those in Texas, however a combination of a strong wind resource, the ability to develop transmission entirely within the state, and Texas' regulatory atmosphere which promotes the development of industrial infrastructure have resulted in more rapid development of wind resources in Texas than elsewhere in the U.S.. Furthermore, a decision in 2007 by the Texas Legislature authorized the PUC to develop and execute a plan to build transmission infrastructure in remote areas of Texas with high wind and solar generation potential called Competitive Renewable Energy Zones (CREZ). The PUC eventually authorized the development of transmission projects that will allow for the development of an additional 8,000 MW of wind energy in West Texas and the Texas Panhandle region. Since wind energy output in this region is highest at night and lowest during the day it is likely that the new transmission infrastructure will also serve a substantial amount of solar power, which is strongest in the West Texas region.

The potential for these policies to enable a rapid expansion of renewable energy within a short period of time provides with a useful basis from which to examine EV emissions tradeoffs scenarios under different generation portfolio assumptions. Limiting this analysis to ERCOT provides several important advantages: transmission of wind and solar energy output is constrained by the physical boundaries of the ERCOT grid, simplifying the analysis and avoiding associated 'emissions leakage issues'; ERCOT is big enough to be a suitable snapshot of the nation as a whole, but small enough to analyze; and ERCOT has the highest level of wind generation as a percentage of total system demand of any grid in the continental U.S.

1.6) Document Scope

The research contained in this thesis evaluates emissions impacts associated with the potential increased use of EVs and renewable energy, and associated societal impacts quantified using a basic cost/benefit economic analysis. Chapter 1 introduces the fundamental motivations for this research and the analytical approach used. Chapter 2 provides relevant background information regarding the technology, policy and analytical issues that inform this research. Chapter 3 discusses in detail the methods used for this research and analysis, Chapter 4 presents the results of this research and Chapter 5 provides the conclusions drawn from these results as well a closing thoughts and areas of needing further research.

2) Background

2.1) Electric Vehicle Policy and Technology Background

Analyses that evaluate emissions impacts related to electric generation, including those evaluating EV charging emissions impacts, can generally be broken into three primary categories based on how they approach emission rate analysis:

- System average emission rates
- Marginal emission rates
- Plant addition/retirement emission rates

Many broad, high-level analyses evaluate EV emissions impacts with the use of some form of simple average emission rates, in which the annual average emission rate of a region is calculated based on the emissions of EGUs within the region. This approach has been used for national, regional, and state level analyses of emission tradeoffs with EVs and has the benefit of providing a simple approach to inform policy makers. Unfortunately this approach lacks temporal resolution, thus fails to capture potentially important impacts that EV charging times may have on the continually changing nature of electric generation mix within a service territory.

In addition to identifying long-term emissions impacts, temporal resolution is necessary to identify near-term air quality impacts, particularly related to NO_x and other pollutants which contribute to the formation of ground level ozone. Several studies have indicated that shifting the source of emissions from daytime ICE emissions to night time EV charging emissions can reduce the formation of daytime ground level ozone (Thompson, Webber, & Allen, 2009), (Thompson, King, Allen, & Webber, 2011). Such an analysis is beyond the scope of this work, however our results may be used to expand such analyses to include potential changes to the electric grid fuel mix, providing useful insight into future air quality impacts.

Several academic analyses have used regression modeling to determine marginal emission rates, applying their results to the impact of increased EV charging load on the electric grid as well as the addition of low-carbon renewable energy generation (Joshua S. Graff Zivin, 2012). This approach has the benefit of providing a more complete picture of the immediate impact EV charging and renewables usage is likely to have on system emissions as a result of their effect on output from specific electric generators. This approach is useful when evaluating impacts for the purposes of compliance with environmental regulations, such as the Clean Air Act, where state or federal agencies are often required to account for immediate emissions impacts resulting from a particular action. Unfortunately because the marginal emission rate approach is often based on historical generation patterns it might not be relevant in longer-term forward-looking analyses in which the changing electric generation fleet is likely to significantly influence results.

Since 2007 the body of analysis examining the impact of transportation electrification on greenhouse gas emissions has grown to include national, regional and state level analyses with varying levels of detail. The most rigorous studies have taken into account emissions tradeoffs associated with electric vehicle charging, comparing the emissions associated with charging to emissions from a conventional internal combustion engine (ICE) performing similar duties. This research extends this approach using detailed generator-level hourly emissions data from the Environmental Protection Agency's (EPA) Continuous Emissions Monitoring System (CEMS), unit commitment and dispatch (UC&D) modeling, and a combination of real-world and simulated EV charging data.

2.1) EV Emissions Tradeoffs Literature Review

Several important studies have dealt with the question of emissions tradeoffs related to EVs, that is: what is the total emissions impact of substituting EV transportation for ICE transportation in the Light Duty Vehicle (LDV) sector? The broad difference in emissions between generators with different fuel types, and even among generators with similar fuel types but different generation and emission control technologies requires a detailed approach incorporating this EGU heterogeneity.

Regional differences are important in this analysis as well: the ERCOT region has a higher proportion of natural gas and wind generation than many other regions in the U.S., as a result EVs charged using the ERCOT fleet may have lower associated emissions. A Union of Concern Scientists study (Anair & Mahmassani, 2012) examined the impacts of regional variations in generation fleets on the emissions associated with EV charging and found in some regions, associated emissions may exceed emissions from a comparable ICE vehicle. As a result these findings are somewhat limited in their application; however this analytical approach and findings regarding the impact of decarbonization of the electric grid on EV emissions are useful regardless of the regional focus.

2.1.1) EPRI/NRDC Analysis

The increasing prevalence of merchant generation ownership and market forces to drive EGU dispatch decision-making as opposed to a single monopoly ownership and dispatch further complicates the analysis. Previous studies have incorporated these complexities to a varying degree, with the level of detail generally increasing among more recent studies. Early analyses, such as the EPRI/NRDC paper "Environmental Assessment of Plug-In Hybrid Electric Vehicles" Vol. 1 ((EPRI/NRDC, 2007)) used engineering based modeling of EV efficiency in terms of kWh/mi with estimates of national average electric generation fleet emission rates in 2050. This study benefitted from a long-term electric generation fleet projection, which is more relevant to policy planners focused on long term impacts. The study employs a detailed electric-sector simulation using a combination of capacity additions/retirements with economic dispatch modeling to evaluate the marginal emissions impact of EV charging.

The approach used in this thesis is similar to the EPRI/NRDC analysis in several regards; specifically in the use of future generation mix scenarios and dispatch modeling to estimate the marginal emissions impact of EV charging. This analysis benefits from the advent of commercially available EVs, along with the associated real-world charging data, which provide real-world examples of both EV charging and efficiency from which to evaluate emission tradeoffs. In addition the model used in this thesis employs dynamic emission rates for individual existing EGUs, derived from the EPA's CEMS database, whereas the EPRI/NRDC approach simulates aggregated composite EGU data for dispatch modeling.

2.1.2) UCS Analysis

While the EPRI/NRDC analysis provided emission tradeoff estimates in a variety of scenarios that could be applied based on different regional characteristics, results were presented using national average impacts. More recent studies have focused on regional differences in electric generation fleets to evaluate the relative benefits of EV usage. The Union of Concerned Scientists developed a high level analysis of regional differences in EV emissions tradeoffs, rating regions as “Good,” “Better,” and “Best” based on the annual electric sector GHG emissions in each region and the resulting estimated emissions from EV charging. While this approach lacks the detail of a marginal emissions analysis using either regression analysis or dispatch modeling, the UCS paper creates a useful metric for the evaluation of EV emission tradeoffs, “mpg_{ghg}.” This metric is intended to provide a standardized unit of comparison between EV emissions and ICE emissions “by determining how many miles per gallon a gasoline powered vehicle would need to achieve in order to match the global warming emissions of an EV” (Anair & Mahmassani, 2012). This metric is used in discussing CO_2 emission tradeoffs between EV and ICE usage as it provides a helpful, commonly understood measurement for EVs.

2.1.3) Yang & McCarthy Analysis

In (Yang & McCarthy, 2009) the authors use a spreadsheet based dispatch model to examine emissions impacts of EV charging in California using EPA’s eGRID database, which provides annual emissions and performance factors for EGUs. The authors identify critically flawed assumptions from policymakers, namely the emissions rate for electricity used to charge EVs based on time of consumptions, and the fact that due to ramping constraints in the near term, natural gas combustion turbine (NGCT) plants may provide a substantial portion of EV fuel. NGCT generating units operate at a lower efficiency than NG combined cycle (NGCC) generating units, which are assumed by CA policymakers to be the exclusive source of electricity for EVs in the near term, leading to an overestimation of the emission reductions achieved by EV usage. McCarthy and Yang's findings highlight the continuing importance of refining such analyses to inform future transportation policy efforts, however as it is based on the current generation fleet mix in a state that is rapidly expanding low carbon electric generation (GTM Research, 2013) it is important to take into account such shifting dynamics.

2.1.4 Analyses Using EPA CEMS Data

More recent analyses of regional electric generation emissions have incorporated data from the EPA's CEMS database, including the studies discussed in the analysis of the secondary emissions impacts of renewable energy generation. In Zivin (2012), the author uses such an approach to develop a regression-based analysis of regional marginal emission rates, using that analysis to evaluate EV emission tradeoffs and highlight other opportunities for policymakers such as identifying the marginal emission benefit of introducing new wind or solar generation to a regional generation fleet. The regression analysis approach has the benefit of incorporating unobserved influences on electric generator dispatch such as operating and transmission constraints. The primary limitation of this approach is its basis on historical EGU performance to evaluate scenarios that generally apply 10 years out or more, at which point the generation fleet may look substantially different. Early EV penetration is likely to follow an exponential function (Thomas A. Becker, 2009) and (Balducc, 2008); as a result analyses of emissions impacts using current generation mix assumptions are likely to be less relevant in the long term policy context, particularly related to greenhouse gas emissions.

2.2) Renewable Energy Policy and Technology Background

It has been hypothesized that renewable generation such as wind and solar can increase emissions rates of pollutants, despite the low emissions of the wind turbines and solar panels themselves. The variable nature of wind and solar energy output means that resources used as firming power must frequently ramp up and down; eventually these may include demand response and energy storage resources, but currently this operation is currently fulfilled by fossil-fueled electric generation units (EGUs) in ERCOT. At the same time, scrubbers used to reduce emissions from fossil-fueled EGUs also are ramped up and down, rather than operating at steady-state conditions. This additional ramping can cause inefficiencies in fossil-fueled EGUs, raising their per-unit fuel consumption and emissions, because some coal fired boilers and their emissions control equipment might lack the flexibility to ramp up and down quickly. This potential for increased emissions from thermal generators as a result of ramping induced by variable power sources from renewables is most often cited in analyses calling into question the benefit of renewable energy in reducing emissions (BENTEK, 2010). For the purposes of this paper this efficiency loss and any resulting emissions impacts is referred to as the "secondary effect" of wind EGU output on emissions.

Researchers at Carnegie Mellon University, including Dr. Jay Apt and Dr. Warren Katzenstein have studied this problem through the application of a theoretical model based on select natural gas generator characteristics, but assumed constant demand in their analysis. (Katzenstein & Apt, 2009)Dr. Joseph Cullen has examined this question as well but did not use time-resolved historical data to establish correlations or causality between wind and emissions rates, focusing instead on identifying specific power plants commonly offset by wind (Cullen, 2011). To the best of the author's knowledge, this work is the first to examine problem of emission rate changes induced by wind energy variability and the resulting impact on net emission reductions from wind in ERCOT using this approach.

The implications of renewable energy on GHG emissions may differ when statistical methods are applied to a theoretical model as opposed to historical data from an interconnected electric grid as in this analysis. Tradeoffs do exist between the two approaches: historical approaches are more tightly grounded in reality, but lose insights into intra-hourly impacts; theoretical approaches can achieve better intra-hourly resolution, which is relevant when contemplating wind power, but are less capable of reflecting a complex, real world system.

Similarly to some studies discussed above, the analysis in this paper addresses the issue of efficiency impacts to fossil fueled EGUs and resulting increases in emissions, defined in this paper as the secondary effect of wind EGU output on emissions). Efficiency is commonly described by the ratio of the heat content (in Btu) by a facility relative to the output (in kWh) of electricity from the facility; this ratio is called "heat rate." Heat rate has an inverse relationship with efficiency: the higher a heat rate, the more fuel must be burned to produce a single kWh and thus the less efficient is the EGU. At the same time, heat rate is positively correlated with emissions rates, as the need to burn more fuel to achieve the same level of electric output leads to greater emissions per unit of energy. For power plants with emissions controls, ramping behavior can influence current emissions in a more complex manner due to delays in heat transfer and control methods, meaning that emission rates will not be as strongly correlated with heat rates as they are in uncontrolled units.

The efficiency of power plants during periods of increasing or decreasing output ("ramping") is referred to as "ramping efficiency." Ramping of EGUs occurs commonly in grid management operations, a result of the need to preserve reliability in the electric grid as demand and power plant outputs vary over time. This relationship is described in (Maddalonia, 2009), with ramping efficiency for coal EGUs generally being lower than ramping efficiency for natural gas EGUs.

Changes in wind generation are a subset of these fluctuations in electric grid characteristics that might cause power plants to operate at suboptimal levels. Other fluctuations are induced by changes in demand by consumers. Operating at suboptimal thermal efficiency can result either from ramping or from consistently level output that is non-optimal for the EGU.

The regression analysis presented in this thesis seeks to evaluate the impact of renewable energy variability on fossil fuel EGU emissions through an examination of detailed historical emissions and heat rates of power plants over time. Using the EPA's

Clean Air Markets Continuous Emissions Monitoring System (CEMS) Database for all reporting EGUs, hourly data for fossil fuel EGUs within the ERCOT electric grid in Texas were analyzed with the intent of determining whether increased wind generation impacted emissions from these power plants. The CEMS database includes CO_2, SO_2 and NO_x emissions as well as fuel use and generation output reported by facility owner and operators on an hourly basis in a manner that incorporates facility inefficiencies during ramping periods, allowing a full evaluation of the emissions reductions achieved in ERCOT as a result of increased wind generation. Additional data from ERCOT with EGU hourly output by fuel type were also analyzed for this research.

2.2.1) Regional Variations in the Role of Renewable Energy in Reducing GHG Emissions

The impact and efficacy of renewable energy in reducing GHG emissions depends largely on regional differences in both renewable resources and regional electric generation portfolios. Variations in solar insolation and wind speed consistency cause substantial inter-regional cost differentials for renewable energy.

Consequently, as generation portfolios vary across regions that have historical different power generation mixes, the effective regional CO_2 emissions rate will also vary, yielding a range of CO_2 emissions reductions per MWh of renewable energy. For instance if wind offsets hydroelectric generation, as in Pacific Northwest, there are essentially no CO_2 emissions reductions; if wind offsets coal generation as in the Midwest, CO_2 emissions reductions will be substantial. In determining the impacts of renewable energy on GHG mitigation, such regional differences in GHG emission reductions must be taken into account. Consequently, this work intends to be geographically-resolved. In the future, it is possible that transmission infrastructure could be used to mitigate this regional differential (for example, wind in Texas could be used to displace Midwestern coal).

A common method for determining GHG emissions avoided by renewable energy is an assessment of marginal CO_2 emissions rates, i.e. the tons of CO_2 for the next MWh of generation needed without renewable energy. This methodology often uses marginal cost and dispatch data to develop an understanding of the marginal unit in a system at any given time, information unavailable at the time of this analysis. The analysis developed by Cullen uses publicly available data to estimate the marginal units offset by wind energy, thereby establishing a marginal emissions profile. Coupled with a more sophisticated model of the emissions rate impacts of system variability such an analysis would provide a comprehensive view of the overall GHG impact of renewable energy.

Table 1. Average CO_2 Emissions Rates of Marginal Units in PJM

pjm

CO_2 Emissions Rates of Marginal Units
Average CO_2 Emissions Rates

(lbs/MWh)		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
2005	Marginal On-Peak	1,952	2,047	2,026	1,986	1,979	1,892	1,897	1,783	1,842	1,948	1,988	1,875	1,934
	Marginal Off-Peak	2,140	2,164	2,155	2,102	2,094	2,077	1,999	1,974	2,074	2,071	2,263	2,177	2,107
	PJM System Average	1,368	1,366	1,311	1,205	1,141	1,290	1,325	1,334	1,306	1,278	1,254	1,285	1,292
2006	Marginal On-Peak	1,976	1,987	1,914	1,987	1,906	1,889	1,831	1,737	1,856	1,808	1,939	2,148	1,912
	Marginal Off-Peak	2,175	2,141	2,140	2,233	2,099	2,081	1,940	1,792	1,987	1,917	2,257	2,321	2,091
	PJM System Average	1,227	1,274	1,306	1,227	1,181	1,226	1,296	1,315	1,213	1,281	1,241	1,205	1,252
2007	Marginal On-Peak	1,946	1,787	1,927	1,843	1,874	1,925	1,988	1,873	1,963	1,932	2,017	1,810	1,908
	Marginal Off-Peak	2,165	1,939	2,086	2,023	2,071	2,023	2,065	2,013	2,071	2,114	2,069	1,969	2,051
	PJM System Average	1,218	1,285	1,256	1,192	1,149	1,240	1,265	1,279	1,259	1,304	1,222	1,212	1,242
2008	Marginal On-Peak	1,982	2,001	2,016	1,946	2,046	2,009	1,961	1,898	1,894	1,933	2,015	2,080	1,981
	Marginal Off-Peak	2,107	2,097	2,138	1,987	2,061	2,052	2,065	1,885	1,976	2,011	2,026	2,070	2,039
	PJM System Average	1,260	1,283	1,266	1,204	1,150	1,231	1,242	1,209	1,188	1,193	1,189	1,197	1,220
2009	Marginal On-Peak	2,015	1,919	1,917	1,853	1,817	1,838	1,875	1,864	1,727	1,604	1,743	1,703	1,823
	Marginal Off-Peak	2,092	1,926	1,964	1,731	1,867	1,876	1,893	1,824	1,721	1,566	1,698	1,817	1,831
	PJM System Average	1,234	1,174	1,105	1,137	1,076	1,112	1,139	1,175	1,065	1,097	1,111	1,179	1,137

Table 1: PJM marginal unit CO_2 emission rates change over time. Source: (PJM, 2010)

Additionally the PJM ISO has undertaken an internal marginal CO_2 rate analysis and presented their findings for use by market participants and PJM members involved in the Regional Greenhouse Gas Initiative (PJM, 2011). Their findings in Table 1 show a higher marginal CO_2 rate during peak times relative to the system average, a departure from the peak emission rates in ERCOT suggested by the regression model used in this paper. These and similar differences in time-dependent marginal CO_2 rates for other regions might have important implications as policymakers consider alternatives to direct regulation of GHG emissions.

2.2.1) National Renewable Energy Laboratory Analysis

In September 2013, the National Renewable Energy Laboratory (NREL) released the most recent study examining the impact of renewable energy intermittency on fossil fuel EGU cycling and associated emissions. NREL assumes a 33% combined level of penetration for wind and solar power in the Western Electricity Coordinating Council (WECC), using the PLEXOS software package to simulate the impacts of additional renewable energy output on the WECC grid (NREL, 2013). NREL uses 2009 EPA CEMS data to model emissions and EGU heat rates combined with detailed wind and solar output profiles to model a variety of renewable energy penetration levels and their impact on fossil fuel EGU emissions and wear and tear. While this approach indicates the potential to incorporate such results endogenously into the PLEXOS simulation of EV charging, the model has not been optimized to accurately reflect the intra-hourly impacts of cycling within ERCOT. Further iterations of this analysis may endogenously model this impact using the current approach to verify results.

In their analysis NREL finds that "CO_2, NO_x, and SO_2 emissions impacts resulting from wind- and solar-induced cycling of fossil-fueled generators are a small percentage of emissions avoided by the wind and solar generation" (NREL, 2013). Specifically, avoided SO_2 emissions are found to increase 2-5% when cycling effects are taken into account, while avoided NO_x emissions are 1-2% lower; the impact to CO_2 emissions is deemed negligible by the authors.

2.2.2) BENTEK Analysis

In "How Less Became More: Wind, Power and Unintended Consequences in the Colorado Energy Market," prepared in 2010 by BENTEK Energy, LLC for the Independent Petroleum Association of Mountain States, BENTEK evaluates the impacts of modulating output from coal-fired power plants to balance grid needs in response to varying wind EGU output (BENTEK, 2010). Examining these impacts for 5 coal-fired units during specific periods of high wind output, BENTEK finds that instantaneous rates for SO_2 increase substantially, while NO_x and CO_2 rates increase somewhat or in some cases not at all.

Extrapolating these results to all hours of the year when wind turbines are generating electricity in Colorado, BENTEK finds that total emissions of SO_2, NO_x and CO_2 are actually increased by the use of wind generation. This methodology has several flaws that have been pointed out by wind energy industry supporters (AWEA, 2011) namely the extrapolation of specific grid characteristics during high wind output periods to the larger Colorado generation portfolio without a clear basis for doing so.

Specifically, in their analysis BENTEK focuses on EGU specific case studies during periods of extreme wind variability, primarily in Colorado during a period when wind generation was a relatively small portion of the state's electricity portfolio. By extrapolating extreme short-period, local events across the state portfolio on an annual basis, BENTEK uses an unrealistic "worst case scenario" in which wind energy is constantly experiencing extreme swings in output, which BENTEK asserts would be exacerbated by further development of wind energy in the state. As discussed below, the analysis from Katzenstein demonstrates that as wind generation grows and is deployed across a geographically diverse region, total wind generation variability is substantially reduced (Katzenstein, Wind Power Variability, Its Cost, and Effect on Power Plant Emissions, 2010).

2.2.3) Katzenstein Analysis

An analysis from Katzenstein (Katzenstein, Wind Power Variability, Its Cost, and Effect on Power Plant Emissions, 2010) contained two important findings contradicting BENTEK's methods and conclusions: 1) geographic diversity substantially reduces the need for frequent ramping of fossil fuel resources, and 2) "Over a wide range of renewable penetration, we find CO_2 emissions achieve ~80% of the emissions reductions expected if the power fluctuations caused no additional emissions." The study draws similar results to an earlier analysis of wind energy in Ireland, (Denny, 2006) which found that CO_2 would be reduced 9% for a wind penetration level of 11%.

Both analyses focus on pairing wind power plants with gas turbines, thus sidestepping the issue of emissions associated with ramping coal-fired units that experience greater reductions in efficiency during ramping periods. (BENTEK, 2010) Furthermore both are based on a detailed modeling of the ramping efficiency of a gas turbine type and associated emissions.

Katzenstein's model is developed using emissions data from natural gas combustion turbines in one minute increments, examining emissions and heat rate changes associated with a generator's deviation from the optimal output. To understand the impacts of wind output changes, the author compares the variability of a single wind EGU with that of up to 20 wind EGUs, finding that 15-minute interval variability is reduced 95% reduction at higher levels of wind penetration. The author uses this analysis to understand the impacts of wind variability using data from natural gas-fired General Electric LM600 combustion turbines and Siemens-Westinghouse 501FD combined cycle EGUs. By pairing varying levels of wind penetration with up to 20 gas-fired EGUs, Katzenstein determined that pairing multiple wind EGUs with multiple gas EGUs is a key strategy to optimize CO_2 reductions.

This approach provides meaningful results; it is important to understand the impacts that variable generation can have on fossil fuel power plants as well as potential strategies for mitigation. The model has its limitations however; this approach inherently assumes static demand, wherein wind EGUs is the only factor introducing variability into the system. Additionally, the emissions analysis is limited to the two natural gas-fired turbines discussed above, while the ERCOT system has a diverse fossil fuel technology portfolio.

2.2.4) Cullen Analysis

The analysis in this thesis adapts the methodology used by Cullen (Cullen, 2011) to estimate the impacts of wind EGU output on individual EGU dispatch decision-making. In a working paper, Cullen develops an econometric model that exploits exogenous changes in wind EGU outputs and other exogenous factors to identify EGUs offset by wind power using observed data rather than simulations. Using these estimates Cullen evaluates the overall emissions impact of wind EGU output using average annual EGU emission rates. The question this analysis seeks to answer is slightly different – rather than focusing on the offset generators this research attempts to determine the marginal impact to the ERCOT system emission rates of wind EGU output.

The Cullen analysis focuses on a period in ERCOT when wind capacity averaged ~3,000 MW whereas during the analysis period used in this thesis, wind capacity averaged closer to 9,000 MW, providing insight into the impacts of greater wind EGU penetration. This distinction raises another important question that will be discussed in further detail later in the paper: the relationship between marginal offsets of CO_2 from EGUs and the longer term impact that low marginal cost wind units may have in shaping the supply curve by impacting the profit margins of EGUs commonly offset by wind output.

As wind output continues to grow it is likely that EGUs commonly offset by lower marginal cost wind resources might fall from the supply stack. Wind energy is likely to remain a low marginal cost resource and to offset EGUs more often during high wind output periods, leading those EGUs to become uneconomic. In this way wind can shape future CO_2 emissions in a manner not accurately reflected in a marginal emission offset approach. However, the Cullen model informs the research used in this paper, providing insight into the impact of wind EGU variability on system-wide emission rates.

2.3) Contributions to the Literature on Electric Vehicles and Renewable Energy

The work in this thesis builds on previous research relating to emissions associated with renewable energy and electric vehicles and adds to the literature in several ways that are intended to illuminate key issues for policy-makers. Fundamentally, this research acknowledges the dynamic nature of the bulk power system and ongoing changes in the fuel mix, incorporating hypothetical decarbonization of the bulk power system into an analysis of emissions associated with future EV charging. In doing so this research includes the "secondary emissions" impacts of increased renewable energy generation, which is particularly relevant when assessing the benefits of EV charging using less carbon-intensive bulk power system.

The dispatch model also presents several improvements over those previously used to evaluate EV emissions, much of which is possible due to the assessment of a limited region used in this analysis. The dispatch modeling approach in this paper uses a more detailed set of assumptions including EGU specific heat input based emission rates which capture changes in emissions due to fossil-fueled EGUs. The model also includes operation constraints for individual EGUs as well as ancillary service market opportunities, which may lead EGUs to limit output to remain available for the provision of ancillary services. While the dispatch model does not include transmission impacts, it does include dispatch of "behind the fence" combined heat and power generation units, which are often difficult to model to due limited reporting on the use of these units. Findings from this research in the ERCOT region demonstrate the relationship between EV emission tradeoffs and changes in electric generation infrastructure generally and as a result are relevant to policymakers throughout the U.S.

This analysis further adds to the literature by combining a marginal emission rate approach with a plant addition/retirement approach to create a forward looking marginal emissions impact analysis which examines changes in system emissions resulting from EV charging and fleet turnover. The model of the ERCOT electric grid used in this research was modified based on prior work (Townsend, 2013) using PLEXOS software to model individual generating unit characteristics including efficiency, emissions, and cost. This model assesses the difference between total system emissions with and without the presence of a large EV fleet. Additionally a set of hypothetical future scenarios and sensitivities is developed which vary the fuel mix, end-user demand and other characteristics of the bulk power system in ERCOT.

While many analyses have been critical in developing a better understanding of the near term implications of electric vehicle usage, the focus of this research is to evaluate the role of EVs in mitigating climate change caused by greenhouse gas emissions, which is an inherently longer-term, occurring over decades rather than years. Electric vehicle adoption has been more rapid to date than hybrid vehicle adoption (Essex & Holand, 2012), however fleet turnover rates indicate that it will be several years before electric vehicles can noticeably reduce greenhouse gas emissions. It may take a decade or more for EVs to induce a meaningful reduction in greenhouse gas emissions from transportation. At the same time the scale of that reduction will depend heavily on the makeup of the electricity generation fleet used to charge those vehicles, which itself has a relatively slow turnover rate, and other factors such as total vehicle miles traveled and the potential growth of mass transit options.

The recent growth of renewable energy generation in the U.S. due to state and federal policies and a continuing decline in capital costs (Bolinger & Wiser, 2011) and (Barbose, Darghouth, Weaver, & Wiser, 2013) indicate a potential for further decarbonization of the electric grid over time. As a result it is important to take into account the possibility of long term changes in both demand for night-time electricity as a result of increased electric vehicle usage, and in the carbon intensity of electricity used to charge EVs. This paper develops a methodology for detailed analysis of such long-term outcomes based on a rigorous analysis of near-term impacts of both EV charging and growth in renewable energy.

3) Analytical Approach

3.1) Summary of Analytical Approach

The approach used in this research consists of a two-part analysis: first the impacts of renewable energy on total systems emissions are estimated, the output from the first analysis informs the second analysis, in which the impact of EV charging on emissions from electric demand in 2025 is estimated. The results from the first analysis come into play in scenarios developed for the second analysis in which renewable generation output is increased substantially, allowing a calculation of the total impact on emissions of the

Diagram 1: Step 1 of Analysis Process

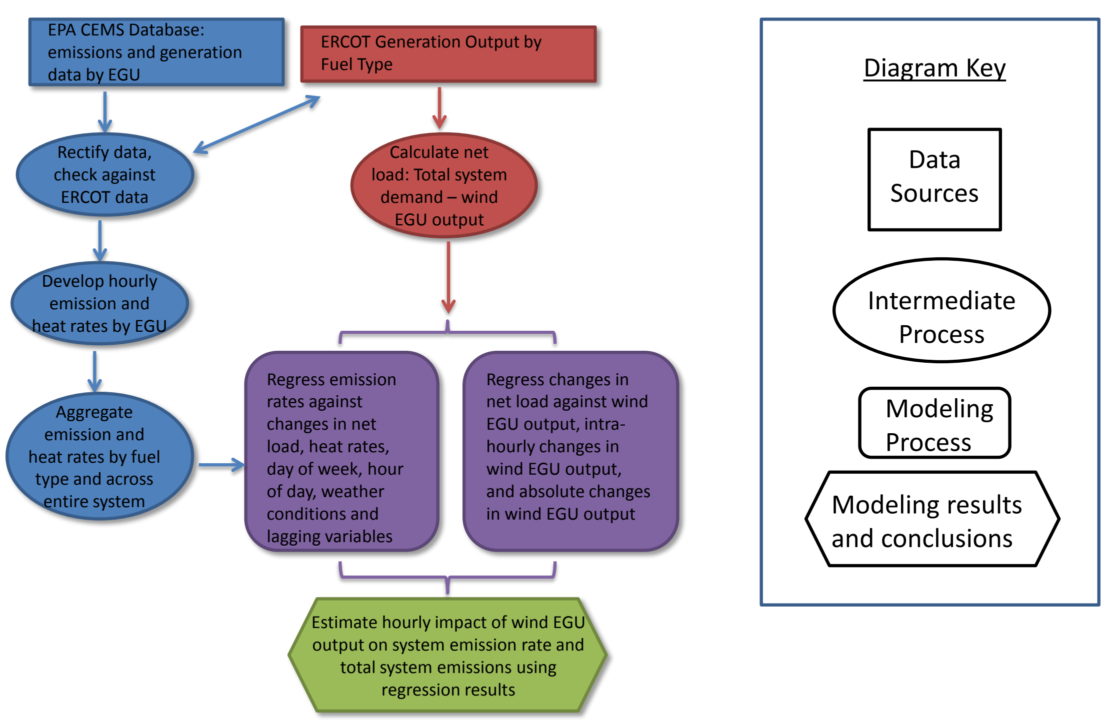
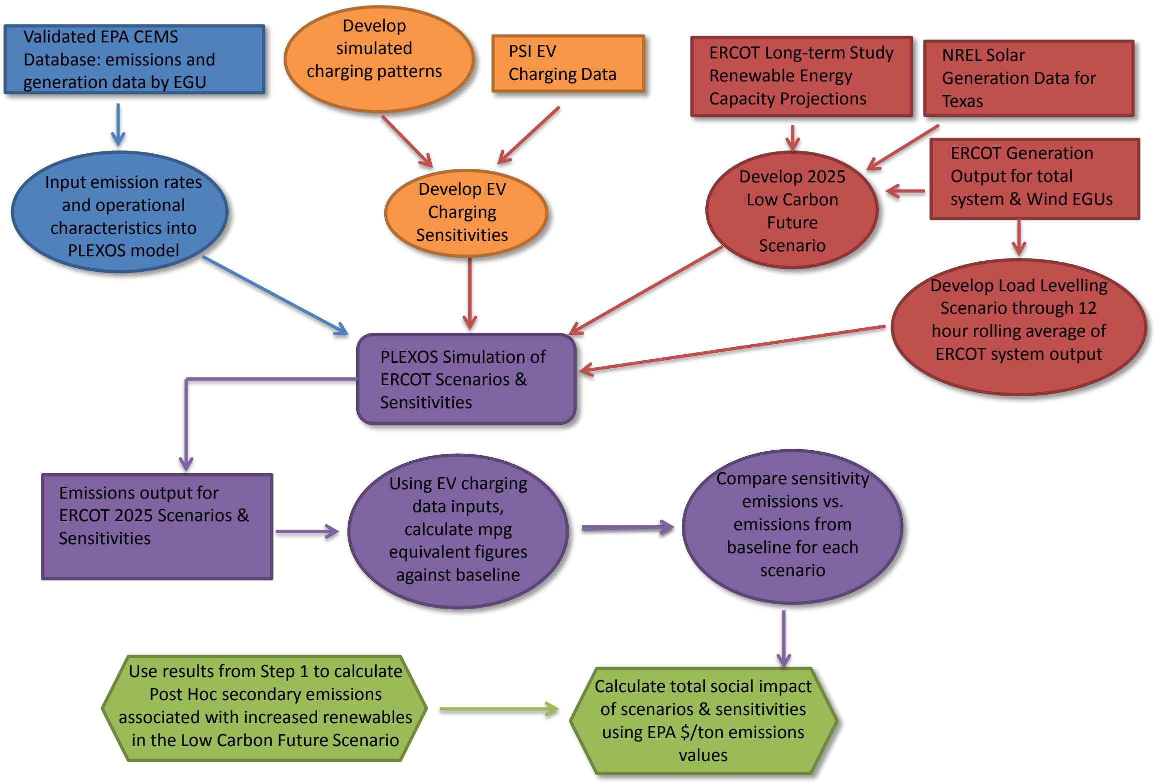


Diagram 2: Step 2 of Analysis Process



Diagrams 1 and 2 above illustrate the two step workflow for this analysis, including major data inputs, processes and intermediate calculations as well as primary modeling analyses and interpretation of results. The regression model in Diagram 1 is the central analysis for the first step, the output of which is combined with the output from the central analysis in Step 2, the PLEXOS simulation. These combined outputs are used to interpret over-arching impacts to emissions of increased renewable energy and EV usage in the ERCOT region.

3.2) Estimating the Impacts of Renewable Energy Generation on Total System Emissions

An important part of this research includes the study of both direct and indirect impacts of wind energy generation on fossil fueled generator emission rates within the same interconnected region. Specifically, the relationship between increased levels of wind energy generation and emissions per unit of electricity produced is explored using historical data for electricity output and CO_2, SO_2 and NO_x emissions in the Electric Reliability Council of Texas (ERCOT). These results are used to inform an analysis of EV emissions impacts under the Low Carbon Future Scenario: to the extent that EV charging reduces wind or solar curtailment further reducing emissions, that amount is decremented based on the findings in this section.

Using EPA's CEMS data, the total combustion emissions of CO_2, SO_2 and NO_x per MWh of electricity output is regressed with wind generation output in the ERCOT system from 2008 – 2011. Through this analysis the primary impact of wind offsetting fossil fuel generation is observed as well as the secondary impact of variable wind energy output on power plant ramping, which may increase emissions.

3.2.1) A Model to Evaluate the Primary and Secondary Emissions Impacts of Intermittent Renewable Energy

This analysis incorporates 15-minute interval power plant output from ERCOT, although it continues to rely upon the EPA's hourly emissions dataset. The combined datasets are used to examine the total net impact of wind energy in offsetting emissions from fossil fuel sources by identifying correlations between increased fossil fuel ramping due wind energy variability.

This portion of the analysis examines several issues:

- The extent to which variations in net load (total load – wind output) exert upward pressure on fossil-fuel EGU emission rates in ERCOT.
- The role wind EGU output plays in the creation of variability in intra-hourly net load.
- The extent to which emissions are impacted by the use of wind generation to offset thermal EGU output.

While thermal generation is used for load balancing in this research, in other regions of the United States (such as the Pacific Northwest) sufficient hydroelectric power capacity exists such that it can be quickly ramped to compensate for wind energy variability. Furthermore, the increasing use of energy storage and demand response as is the case in the Load Leveling scenario (presented later in this chapter), may provide opportunities to compensate for such variability without exacerbating emissions from thermal generators. However, less than 0.5% of electric generation in ERCOT comes from hydroelectric generation, and although energy storage and demand response resources are being developed they are not currently at a stage of deployment to balance wind energy variability. As a result in ERCOT firming power for wind energy generally comes from thermal units.

This analysis focuses on the current infrastructure available in ERCOT using the historical impact of wind generation to project forward impacts of wind and solar generation in the 2025 scenarios. In the analysis used for this paper a simplifying assumption that the primary and secondary impacts of wind energy remain unchanged in 2025 is used.

Emission rates, whether marginal or averaged across all fossil fuel units over a period of time provide an important perspective into the effects of wind energy on fossil fueled EGUs. However, emission rates are only important to the extent that they allow a calculation of total emissions. It is possible for emission rates to increase as a result of ramping induced by wind energy variability but ultimately the impact of wind energy output is to curtail or reduce overall fossil fueled output, thus reducing total net emissions. From a public policy, health and environmental perspective total net emissions determine social benefit and are the final determinant by which the social benefits of wind energy as they relate to emissions must be evaluated. The relationship between emission rates and total emissions can best be described in two equations as follows:

$$EGU\ Hourly\ Emission\ Rate = \frac{\text{EGU hourly emissions}}{\text{EGU hourly MWh}}$$

$$Total\ Hourly\ Emissions = \sum_{EGU=1}^{Total\ \#\ of\ EGUs} EGU\ Hourly\ Output * EGU\ Hourly\ Emission\ Rate$$

Thus, it is possible that wind can cause the emissions intensity of the overall fleet to increase, while simultaneously reducing net emissions. This phenomenon occurs because the wind variability pushes thermal generators into dynamic operation that is sub-optimal while also reducing their output. So, the thermal generators operate less often in steady-state mode (driving up the emissions intensity) and at a lower overall output (driving down the net emissions). Unfortunately, much prior work glosses over these distinctions. This work seeks to rectify that shortcoming.

Other researchers have examined the impact of wind energy on total emissions as well as emission rates using a variety of analytical methods, focusing on ERCOT and other regions with RPS policies. Brief summaries of three of those (Bentek, 2010; Katzenstein, 2010; and Cullen, 2011) are discussed in detail below, with each analysis informing the approach to this problem used in this thesis.

3.2.2) Datasets Used in Analysis

The analysis presented herein uses historical data from the EPA and ERCOT from 2008-2011. While EPA data are only publicly available at an hourly temporal resolution, ERCOT data are available in more highly resolved intervals. For this analysis 15-minute temporally resolved ERCOT generation data is used, allowing the impacts of intra-hourly variations in EGU output on hourly average emission rates and total hourly emissions to be examined. The impacts of variability in wind generation are intra-day, making data with sufficient temporal granularity critical to this analysis. By contrast, annual or monthly data that are often used for renewable energy policy discussions (Jacobson & High, 2008) will not capture the intra-day impact of wind on fossil fuel heat rate and could produce misleading results. Thus, this research relies instead on data with better resolution. The EPA dataset includes heat input, electricity output, emissions of SO_2 ,

NO_x, and CO_2 for all ERCOT facilities required to report data to the EPA under the Clean Air Act.[2]

The time period from 2008-2011 was chosen to analyze the period with the highest level of wind energy output; in 2008 wind energy capacity reached 10% of total ERCOT capacity and 5% of total EGU output. As of 2011 wind has grown to 13% of total capacity and 8.5% of EGU output, making this period ideal for examining the impact of large amounts of wind energy (Chart 1). It is important to note that during this period ERCOT also underwent a significant transition from a zonal dispatch model – one in which EGU dispatch decisions were made by generation owners based on congestion

Chart 1: Growth in Texas Wind Capacity
1999 - 2011

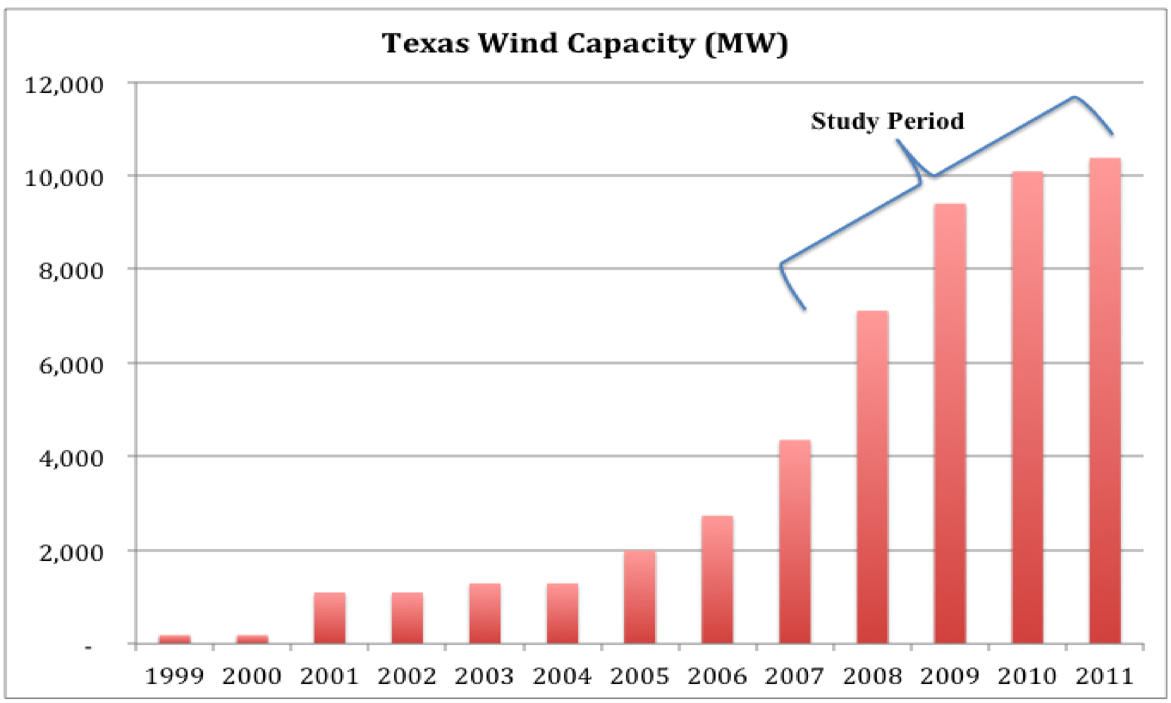


Chart 1: 2008 – 2011 shows substantial increase in wind EGU capacity.

[2] Email conversation with EPA staff

constraints across 5 ERCOT zones – to a nodal market in which dispatch decisions are centrally organized at ERCOT and based on congestion and other factors across more than 4,000 nodes. This new market structure has the potential to shift dispatch decision-making in ways that could alter the impact of wind EGU variability on thermal EGU emission rates, however the impact to this research is likely to be minimal. This analysis focuses on the overall effect of wind generation on the emissions of fossil fuel EGUs; market structure issues, while important to consider when interpreting results, are not the subject of this analysis. Thus, the fact that the markets changed dramatically during the study period should not degrade the value of the analysis.

Generator data was provided by ERCOT on an hourly MWh basis aggregated to the fuel type level and ERCOT zone. While the EPA's heat input and emissions data are critical to this analysis, the ERCOT data provides needed information for non-fossil fuel generation output, in particular nuclear and wind power. Additionally, the EPA dataset only includes information for fossil-fueled EGUs required to report to the EPA under the Clean Air Act. The ERCOT data provides the necessary information to verify the extent to which the EPA dataset represents a comprehensive profile of ERCOT's generation resources by comparing ERCOT's coal and natural gas generation data to the EPA data. The mean difference between these datasets for each 15 minute interval from 2008-2011 is illustrated in the formula:

$$[MWh_{ERCOT}-MWh_{EPA}]/MWh_{ERCOT}$$

Applying this formula to the ERCOT and EPA datasets shows that EPA accounts for 95% of the fossil fueled generation in ERCOT, with a standard deviation from the mean of 5%, indicating that the EPA dataset provides ample data for the purposes of this analysis.

3.2.3) A Note on Timestamps

ERCOT data is provided in "interval ending" time, i.e. the interval 1:00 contains the minutes from 0:46 – 1:00, whereas the EPA data is provided in "hour beginning," where the hour 1:00 contains the minutes from 1:00 – 1:59. This analysis converts the EPA dataset to "hour ending" timestamps, and in this thesis it may be assumed that all intervals, whether hourly or 15 minute, are noted in "interval ending" time unless otherwise specified. In addition, while the ERCOT dataset has been modified so that all intervals are in Central Standard Time (CST), modifications were necessary in the EPA dataset. EPA data is provided in a modified Central Prevailing Time (CPT) format where the "missing" hour resulting from a transition to Central Daylight Time (CDT) is folded into the following hour. As a result, in transitioning the EPA dataset to CST, the 2^{nd} and 3^{rd} hours of the spring and fall transitions between CDT and CST are not included in this analysis to avoid the use of inaccurate or estimated data. ERCOT 15-minute interval data is converted to hourly data by averaging the 15 minute output across each hour.

3.2.4) Developing an Empirical Model

Using EPA's Clean Air Markets hourly emissions data, the most granular data set available of emissions from electric generating units, the total combustion emissions of CO_2, SO_2 and NO_x per MWh of electricity output for the ERCOT system from 2008 – 2011 are calculated. The EPA database includes hourly emissions of CO_2, SO_2 and NO_x in lbs reported by facility owner and operators on an hourly basis in a manner that incorporates facility inefficiencies during ramping periods. The database also includes hourly output for each facility, this research uses those two figures to arrive at a lbs/MWh figure allowing a full evaluation of the CO_2 emissions reductions achieved in ERCOT as a result of increased wind generation. This database is combined with generation output data aggregated by fuel type, provided by ERCOT on a 15 minute interval basis, which is used to determine both total system variability and wind energy output variability on a time dependent basis (Chart 2)

Chart 2. Change in ERCOT Fossil Fuel and Wind EGU Output Over Time

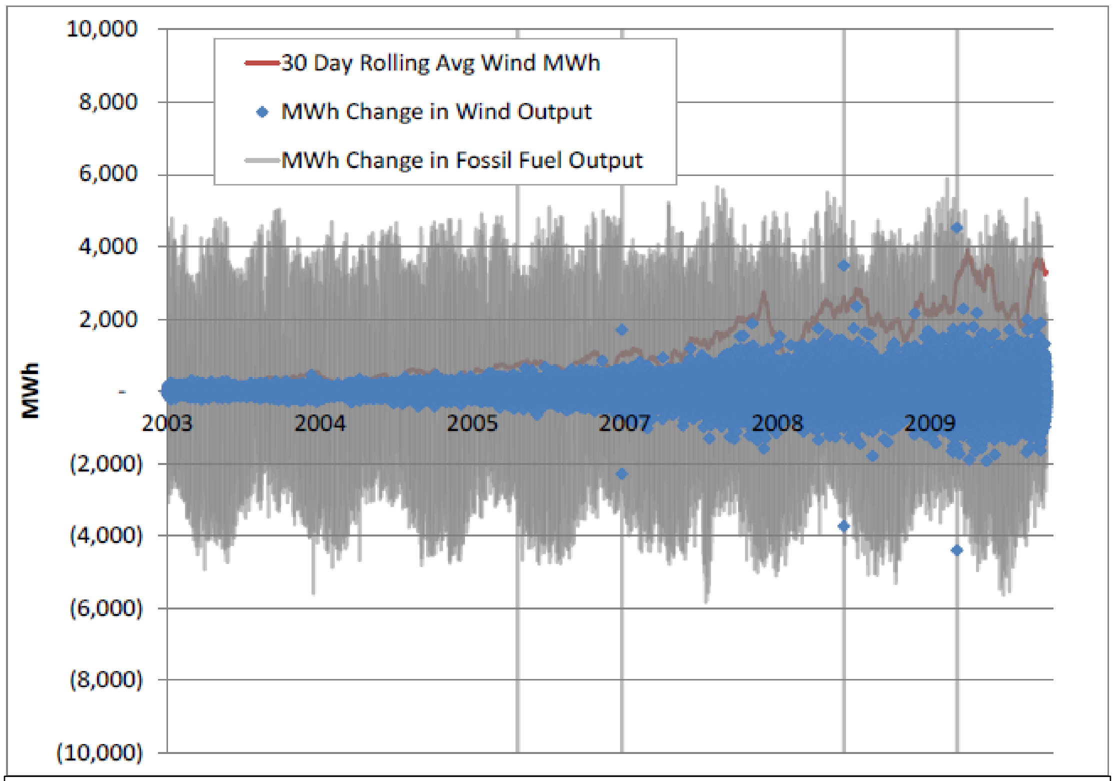


Chart 2 shows the change in fossil fuel output within ERCOT over time, during a period of strong wind growth, and resulting growth in the change in wind EGU output.

Integrating and normalizing the raw data in this way yielded columns of highly resolved information on generation and emissions for every EGU in ERCOT for the entire study period. That curated dataset enables the development of two regression models that examine 1) the role wind energy output variability plays in increasing overall system variability, and 2) the relationship between overall system variability and changes in hourly emission rates aggregated across the system. To the extent that changes in intra-hourly output affect emissions output, those changes will be reflected in the hourly emissions dataset as well.

3.1.5) Modeling Emission Rates

As was noted earlier, a simple average of EPA facility emissions rates fails to capture emissions impacts from individual EGUs as a function of their output and marginal heat rate changes, both of which are important factors for understanding total system emissions. Consequently, weighted average system emissions rates were developed for CO_2 (tons/MWh), SO_2 (lbs/MWh) and NO_x (lbs/MWh) respectively:

$$CO_{2,t} = \frac{\sum_{n=0}^{N} \mathrm{CO2}_{n,t}}{\sum_{n=0}^{N} \mathrm{Output}_{n,t}} \quad SO_{2,t} = \frac{\sum_{n=0}^{N} \mathrm{SO2}_{n,t}}{\sum_{n=0}^{N} \mathrm{Output}_{n,t}}$$

$$NO_{x,t} = \frac{\sum_{n=0}^{N} \mathrm{NOx}_{n,t}}{\sum_{n=0}^{N} \mathrm{Output}_{n,t}}$$

For N = # of ERCOT fossil-fuel EGUs, time t

(1)

In addition to estimating emission rates for each EGU as a function of output the model in this chapter determines average system-wide heat rates for coal and gas-fired EGUs; those heat rates serve as a measure of total system efficiency. In general coal fired facilities have a higher heat rate than natural gas combined cycles, although gas fired combustion turbines tend to have even higher heat rates. Using EPA hourly heat inputs and electricity outputs, hourly heat rates were developed using the following methodology:

$$Heat\ Rate\ \left(\frac{Btu}{kWh}\right) = 1{,}000 \text{ x } \frac{Heat\ Input\ (MMBtu)}{Output\ (MWh)} \tag{2}$$

The issue of intra-interval 'spikes' in emissions, whether within an hourly or 15 minute interval, is often raised during discussions of appropriate methodologies to identify the impact of wind energy or other exogenous factors forcing power plant ramping. As an example, emission spikes might be 'smoothed' as emission rates are averaged over the course of an hour, resulting in a diminished ability to reflect the severity of intra-hourly spikes. Regardless, because such spikes are measured by emission monitoring devices and included in hourly totals, the impact of emission rate spikes on total hourly emissions is captured in this analysis. When monitoring emissions for public health reasons (related to asthma, etc.), hourly NO_x emission data is suitable because ozone forms over a timespan of hours, not minutes, thus sensors that integrate (or sum) emissions over hourly intervals provide sufficient data for the purposes of this research. For SO_2 and CO_2, hourly resolution is also sufficient as the impacts of SO_2 and CO_2 on acid rain and climate change respectively are the result of accumultation of emissions over a timespan of years. In some cases spikes may be more extreme than can be captured by installed monitoring systems, however existing EPA measurement standards require that the "span value" of a monitor be set at or above the maximum potential concentration of the relevant gas (EPA, 2009).

3.2.5) Applied Regression Models

The focus for this study is to develop a more refined version of the model used in earlier work (Meehan, 2012), which includes the decoupling of wind output's impact on net load as well as the impact of net load variability on system emission rates. In addition potential non-linear relationships between the change in wind EGU output, change in net load and CO_2 emission rates are modeled. The intent in decoupling regression models is to better understand any causal relationship between changes in net load and CO_2 emission rates, while isolating the impact of wind EGU output within variations in net load.

In order to account for exogenous weather impact on net load, specifically temperature responsive demand, hourly temperature readings from 8 major cities in Texas are included as well as a simple hourly average of those temperatures. To further account for exogenous factors 15 minute interval lagging variables for net load over the prior 2 hours are incorporated. Finally the dummy variable set is expanded to include day of week, hour of day and month of year.

As a first step in this analysis the impact of net load ($\Delta\gamma$) on emission rates (as defined above) is defined for time *t* as:

$$\Delta\gamma_t = System\ MWh_t - MWh\ wind_t \tag{3}$$

The first model seeks to identify the impact that variability in net load has on CO_2 emission rates for all units in the EPA dataset:

Equation 4:

CO_2 *Emissions Rate* $= \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \ldots + \beta_{49} x_{49} + \beta_{50} x_{50}$

where:

$x_1 = \gamma$

$x_2 = \Delta\gamma_t = \gamma_t - \gamma_{t-1}$

$x_3 = \Delta\gamma^2$

x_4 = *system heat rate*

$x_5 \ldots x_{10}$ = *day of week* → *i.e.* $x_5 = 1$ *if Monday, etc.*

$x_{11} \ldots x_{33}$ = *hour of day* → *i.e.* $x_{11} = 1$ *if hour = 1, etc.*

$x_{34} \ldots x_{42}$ = *temperatures for 8 select cities and system average temp*

$x_{43} \ldots x_{50} = \gamma$ *lagging variables for prior 8 periods (2 hours)*

(4)

The second model seeks to identify the impact that wind EGU output has on changes in γ:

Equation 5:

$\Delta\gamma = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_{41} x_{41} + \beta_{42} x_{42}$

where:

x_1 = *wind EGU output*

$x_2 = \Delta wind = wind_t - wind_{t-1}$

$x_3 = \Delta wind^2$

x_4 = *system heat rate*

$x_5 \ldots x_{10}$ = *day of week*

$x_{11} \ldots x_{33}$ = *hour of day*

$x_{34} \ldots x_{42}$ = *temperatures for 8 select cities and system average temp*

(5)

Distribution for both CO_2 emission rates and change in net load follow a normal distribution pattern although CO_2 emissions (Chart 3) are slightly skewed and change in net load has minimal spread with several extreme outliers, though the frequency of those outliers is too low to observe visually in Fig. 5. This Gaussian distribution characteristic indicates both dependent variables are suitable candidates for regression analysis.

Chart 3: System CO_2 Emission

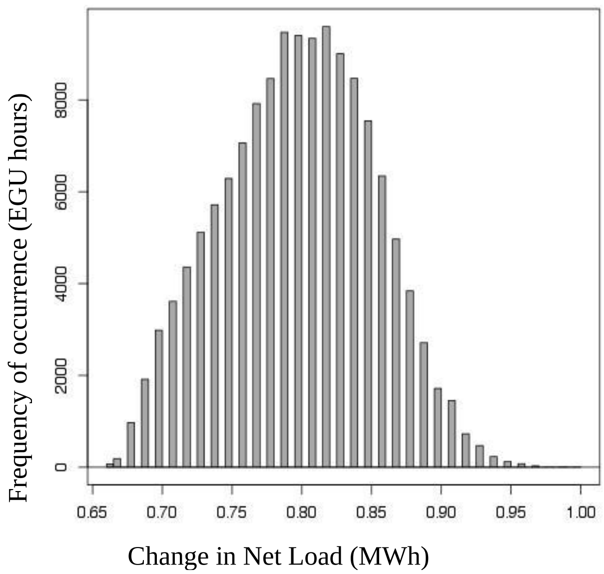


Chart 3: CO_2 emission rates are normally distributed

Chart 4: ERCOT $\Delta\gamma$, 2008-2011

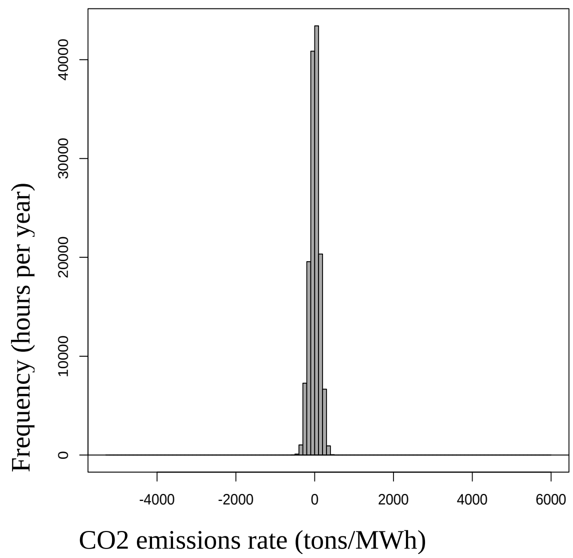


Chart 4: ERCOT changes in net load ($\Delta\gamma$) are normally distributed with minimal spread

While the primary goal of this analysis is to understand secondary impacts to system wide CO_2 emissions this model may be applied more specifically to thermal EGUs to understand the impact that $\Delta\gamma$ and Δ*wind* may have on specific units. In Cullen (2011), ten thermal EGUs in ERCOT are identified as being offset by wind EGU output the most often, and although the Cullen analysis looks at a timeframe of higher marginal cost for natural gas units – thus placing some natural gas units on the margin – and lower wind penetration, most of the units listed in his analysis are still in use.

Of these units, several exhibit characteristics that make them non-optimal for modeling purposes, including non-Gaussian emission rate distributions and low capacity factors. Low capacity factors indicate both that there might be too few data points available from the unit to develop a robust model, and that the units are conventional ‘peaking’ units, meaning that a number of exogenous factors beyond wind EGU output are likely to force these units to ramp.   Filtering for these units, only coal-fired units identified in the Cullen paper are candidates for such an analysis; however the 5 coal-fired units do account for 69% of total emissions offset by the top ten units.   The research in this thesis includes an analysis using two modified versions of the Cullen approach in which CO_2 emissions from coal and gas are considered in separate models. Due to the different operating characteristics of each resource, examining the potential impact of wind generation on each provides useful insights into how or whether wind variability impacts one resource more than the other.

It is worth examining emissions of NO_x and SO_2 independently of CO_2 because of the concern that emissions controls might experience inefficiencies and time lags that would exacerbate the impact of heat rate increases (Katzenstein & Apt, 2009). Increased output of variable wind and solar EGUs intended to mitigate global warming impacts of CO_2 may result in unintended consequences. Primary among these unexpected impacts are increases in emission rates or total emissions of NO_x and SO_2. The methodology used to estimate CO_2 impacts is repeated for NO_x and SO_2, as a result this research addresses some concerns related to unintended consequences, discussed in Chapter 4.

3.3) Estimating the Impact of EV Charging on Electric Demand in 2025

3.3.1) Description of the PLEXOS Unit Commitment & Dispatch model

The PLEXOS for Power Systems Unit Commitment & Dispatch (UC&D) model was used in this analysis to evaluate the impact to electric generation emissions within ERCOT as a result of EV charging. The model is a commercial software package published by Energy Exemplar than can perform a variety of optimization-based functions for electricity markets and operations. PLEXOS offers academic licenses and is capable of unit commitment and dispatch modeling, capacity expansion planning, maintenance planning and stochastic optimization. Only the unit commitment and dispatch capabilities are used in this analysis, which optimize power plant operations across the fleet to meet energy demand based on a series of performance and cost criteria. PLEXOS version 6.300 R03x64 was used for this analysis.

PLEXOS optimizes generation fleet operation through a two-step process, with the first step occurring over a number of user-specified medium-term (MT) time frames and the second step over a (larger) number of user-specified short-term (ST) time frames. The model has been developed and published in prior work, with a more detailed discussion of general inputs to the model in (Townsend, 2013). The PLEXOS simulation builds on the Townsend work and accounts for a variety of ancillary services markets available to generators in ERCOT and the impact of those markets on generator dispatch optimization. In addition the model optimizes dispatch for so called “behind the fence” generation used for combined heat and power operations (CHP).   These facilities can be difficult to model as they often have incentives derived from non-modeled markets and because ERCOT identifies them only as “Private Use Networks” make the identification and characterization of these units on an individual basis difficult. The transmission infrastructure is modeled using a simplified ‘copper sheet’ approach in which transmission system capacity is assumed to exceed system needs at all times. This work adds several features to the model, including updated, unit specific emissions data from the EPA's CEMS data, along with simulated wind and solar energy generation and power plant retirements in 2025 for the LCF scenarios.

Renewable energy generation was simulated using the "Updated Wind Curves" scenario of ERCOT's Long-Term System Assessment (LTSA), published in 2013 which includes "Updated wind patterns reflecting recent improvements in wind turbine technologies") (ERCOT, 2012). ERCOT's LTSA provides system planners and regulators with a 10 to 20 year forward-looking assessment of system infrastructure changes and needs. The report is primarily focused on transmission infrastructure needs, which are met through a centralized approval and cost-recovery process regulated by the Texas Public Utilities Commission.

For ERCOT to understand transmission needs it is necessary to model generation fleet changes over times and the LTSA offers a realistic forward-looking analysis that is useful for the LCF scenarios. In ERCOT's "Updated Wind Curves" scenario, 6,500 MW of solar generation and an additional 9,259 MW of wind energy are installed by 2025. Based on this projection and current wind energy capacity the model assumes a total wind energy capacity of 20,000 MW in the ERCOT footprint.

Hourly wind generation patterns from 2011 were scaled to represent the increase in generating capacity within ERCOT using the simplifying assumption that wind generating capacity will have a similar geographical distribution in 2025 to that in 2011. It is important to note that since 2009 the geographic distribution of wind capacity in ERCOT has begun to shift toward coastal wind generation, which has the benefits of being closer to regions of high demand and having a generation profile that aligns better with peak demand. Based on recent trends it is reasonable to expect that this approach underestimates the amount of coastal wind growth expected over the next decade. ERCOT's LTSA makes a similar simplifying assumption, indicating that the level of wind generation projected in their analysis is primarily expected to be developed in west Texas in the CREZ transmission areas. This assumption is necessary due to the lack of geographically disaggregated wind generation data in the data provided from ERCOT, however in most scenarios EV charging occurs at night; during hours that west Texas wind is more likely to be a factor than coastal wind.

In 2011 the only utility scale solar project in operation was San Antonio City Public Service's (CPS) Blue Wing Solar Farm (CPS Energy, 2013), which is not included in the unit commitment and dispatch model. As a result there is no production data available to model output from the 6,500 MW of solar generating capacity in 2025 for the LCF scenarios. To model this output the National Renewable Energy Laboratory's (NREL) PVWatts calculator is used, which provides hourly solar output based on "typical meteorological year" (TMY) data. To determine solar generation data PVWatts output is modeled based on an installation in San Angelo, TX, which represents a notional mid-point between the solar rich areas in west Texas and the load centers for ERCOT, where most large solar projects have been installed to date. Single-axis tracking ground mounted solar panels were modeled--despite the fact that dual axis trackers provide more solar output and are increasingly common for larger solar installations -- to maintain a conservative output estimate.

Wind and Solar generation are effectively 'price-takers' in the ERCOT market, due to extremely low variable costs and the marginal clearing price construct, which pays all generators at the clearing price. Usually this is based on the marginal cost of the marginal generating unit at a given point in time, since marginal costs for wind and solar are below the marginal cost of almost all other generating units on the system, when those renewable resources are available they will generate at most clearing prices. In our analysis neither wind nor solar EGUs are curtailed due to system constraints or low marginal prices. As a result, in our LCF scenario, renewable energy generates at available capacity and is not affected across scenarios which model a single year.

The LCF scenarios includes the retirement of a number of power plants by 2025 based on a combination of ERCOT's LTSA and publicly stated plans of generation owners. In ERCOT's LTSA "Retirement Scenario" natural gas units over 50 years old are retired in an attempt to model recent trends and concerns such as the idling or retirement of several older gas generating units and the potential implementation of federal cooling water intake structure requirements. ERCOT did not model coal unit retirements because most coal-fired facilities are not located in or near EPA Clean Air Act non-attainment zones, making them ideal for brownfield redevelopment even if the coal units are retired. While this assumption is understandable for the purposes of modeling stresses to the transmission system, it is not sufficient for the purposes of this analysis.

As a result the LCF model includes the retirement of CPS's JT Deely Power Plant, which has been publicly announced, and of several lignite coal units (2 units from

Monticello and Martin Lake Power plants) which are currently only being operated by their owner during the summer peak usage season. Such seasonal idling indicates that the units are not cost competitive in the ERCOT market during shoulder months; the advent of additional wind and solar power as well as expected EPA regulations of carbon dioxide emissions are likely to further reduce their cost-competitiveness.

3.3.2) Estimating Electric Vehicle Adoption

In order to effectively model scenarios in 2025 it is necessary to estimate the amount of electric vehicles in use within the ERCOT service territory. This estimate is intended as a mechanism to aid evaluation of the emissions impact EVs are likely to have given a substantial level of EV usage and not as a prediction of EV market penetration in 2025. Several studies have developed models to simulate expected growth levels for EVs in the U.S., including (Thomas A. Becker, 2009), who project that EVs will account for 45% of light duty vehicle sales by 2025 in their reference case. However specific data such as total EV ownership is not offered for 2025. This projection is based on a variety of baseline economic assumptions including oil prices, manufacturing cost and new technology adoption rates. In their study they find that growth increases exponentially, meaning that sales grow from 450 thousand EVs in 2015 to 2.7 million in 2020, a pattern which tracks roughly with historical patterns for hybrid vehicle sales.

A comparative analysis of hybrid vehicle sales over time with EV sales from 2011-2013 YTD shows that EV sales have followed a similar initial pattern thus far with total sales in years 1, 2, and 3 (YTD) being roughly double the sales of hybrids in the 1st, 2nd, and 3rd year of sales. Extending this relationship through 2025 cumulative EV sales would reach almost 8 million by 2025, as seen in Chart 5 (U.S. Department of Energy, 2011), (Cobb, December 2011 Dashboard: Sales Still Climbing, 2012a), (Cobb,

Chart 5. Historical hybrid sales used to project future EV sales

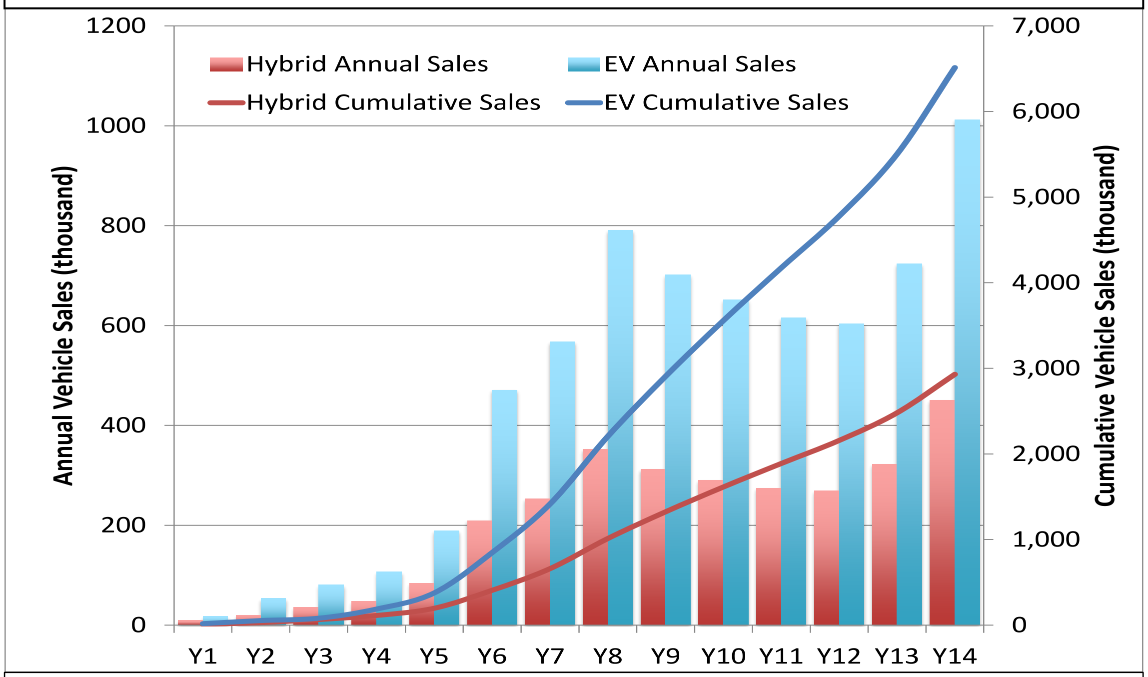


Chart 5 above shows the historical growth pattern of hybrid vehicle sales in the U.S., and projected EV sales growth in the U.S. given known sales through September 2013. This chart assumes EV sales follow a growth pattern similar to historical hybrid vehicle sales. Year 1 is 2000 and 2011 for Hybrid sales and EV sales

September 2012 Dashboard, 2012b), (Cobb, December 2012 Dashboard, 2013), and (Shahan, 2013). A number of additional analyses produce a variety of forecasts; however for the purposes of this analysis only an approximation is necessary to model emissions tradeoff on a per-vehicle basis. According to Experian Automotive, Texas accounted for 5.02% of hybrid sales nationally in 2012 (Goldfein, 2013). This analysis employs a simplifying assumption that EV sales in Texas mirror hybrid sales as a fraction of total U.S. sales throughout the analysis period. ERCOT serves approximately 23 million consumers in Texas (ERCOT, 2013), which has a population of 26 million (U.S. Department of Commerce, 2013), resulting in an estimate of approximately 350,000 EVs in Texas by 2025 for the purposes of calculating the impact of EV charging on hourly demand.

As discussed in Section 3.2.3, several modeling scenarios rely on EV charging data from Pecan Street Inc.'s Mueller Energy Internet Demonstration Pilot (PSI data). Pecan Street, Inc is a research and development organization headquartered at the University of Texas at Austin, the organization develops and tests advanced technology and customer behavior related to energy use. As part of their work Pecan Street, Inc. has supported the deployment of over 60 EVs in the Mueller residential neighborhood located in Austin, TX and measures a variety of statistics related to EV owner usage including detailed charging data (Rhodes & al., 2014 (accepted)). The PSI data uses charging behavior from participants in Pecan Streets demonstration project, which included data from approximately 35 Chevy Volts and 8 Nissan Leafs from September 2012 through August of 2013. Charging was measured on one-minute intervals, however to integrate these data into the PLEXOS model, PSI data were aggregated on a seasonal, day-of-week, and hourly basis to avoid over-reliance on a small sample set.

The analysis uses the PSI data combined with the estimate of EV penetration levels in Texas by 2025 to scale up EV customer charging patterns estimating the hourly impact to demand EVs being charged on a regular basis. Using empirical data for both EV charging and electric grid carbon this paper focuses on the use of light duty electric vehicles, primarily the Chevy Volt, and electric grid characteristics in the Electric Reliability Council of Texas (ERCOT) footprint. This research uses the notional estimate of EV usage in 2025 to develop three "primary" scenarios: a Base Case which essentially mirrors today's ERCOT generation fleet mix projected through 2025, a "Low Carbon Future" scenario in which the generation mix is shifted towards greater use of renewable energy, and a "Load Leveling" scenario in which the market uses demand response and energy storage to reduce intra-daily variations in load.

3.3.3) Modeling Scenarios

Scenarios modeled in the PLEXOS simulation are the central analysis to this research, providing insight into the emissions impact resulting from a variety of assumptions using the CEMS 2011 database as well as the analysis of the secondary impacts of wind generation on fossil fuel emissions.

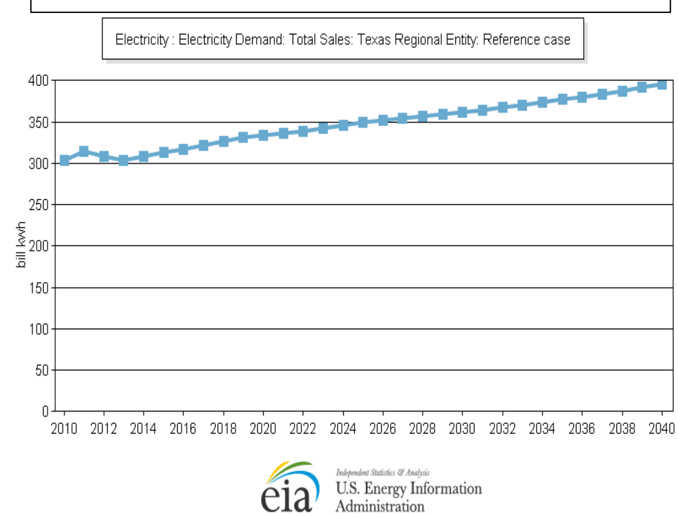
Table 2. Scenarios and Sensitivities Modeled

	Base Case	Load Leveling	Low Carbon Future
Base Case	EVBC	LLBC	LCFBC
PSI Charging Data - Volt	EVPSIV	LLPSIV	LCFPSIV
Standard Charging - Volt	EVSV	LLSV	LCFSV
Quick Charging - Volt	EVQV	LLQV	LCFQV
Averaged Charging - Volt	EVAV	LLAV	LCFAV
PSI Charging Data - Leaf	EVPSIL		
Standard Charging - Leaf	EVSL		
Quick Charging - Leaf	EVQL		
Averaged Charging - Leaf	EVAL		

Table 2 shows the abbreviations used to identify the scenarios discussed throughout this paper

The secondary emissions impacts of wind generation are important to incorporate to accurately compare the net emissions resulting from EV and ICE transportation. The approach used in this thesis is to begin with a model of a 2025 “Base Case,” based on the model used in (Townsend, 2013), using the EIA’s 2013 Annual Energy Outlook AEO Reference Case demand growth projections through 2025 for the Texas Regional Entity, a regulatory body solely covering ERCOT’s footprint. This case is contrasted against the other primary scenarios, which represent changes to the ERCOT marketplace beyond EV charging impact: the “load leveling” scenarios and “low carbon future” scenarios. Each primary scenario is modeled first using Base Case hourly electric demand assumptions, and then using a variety of EV charging scenarios in order to quantify the impact of EV charging on system emissions given a variety of future market conditions.

Chart 6. Projected Growth in Demand in the ERCOT Region



To develop the Base Case (BC), Low Carbon Future (LCF) and Load Leveling (LL) scenarios this analysis uses a combination of data provided by ERCOT, the Energy Information Administration (EIA) and the Environmental Protection Agency (EPA). All scenarios take place in 2025 with total energy demand growing at a rate of approximately 0.8% annually, as derived from total electricity sales in the Texas Regional Entity (the service territory of ERCOT) in the EIA's 2013 Annual Energy Outlook (AEO) (U.S. Department of Energy, 2013a). Chart 6 shows the expected growth in electricity sales in ERCOT under the AEO Reference Case through 2040. The BC and LCF scenarios assume that hourly demand patterns remain unaltered in 2025, while the LL scenario assumes a notional smoothing out of hourly demand using a 12 hour rolling average of the hourly demand assumed in BC and LCF scenarios.

3.3.3.1) Base Case Scenario

This scenario is intended to represent a future in which the ERCOT marketplace is largely unchanged from today in terms of generation fleet makeup and electric demand. Using the AEO's Reference Case growth rate of approximately 0.8% annually the 2011 hourly load curve is scaled to match 2025 annual load projections for the Base Case scenario, assuming no change in hourly load shapes. The model for supply in this and the Load Leveling scenarios uses ERCOT's current generation portfolio with heat rate based emissions data by electric generating unit (EGU) provided by the EPA CEMS database.

Since demand in 2025 will likely exceed the capabilities of ERCOT's current generation fleet, this scenario includes the hypothetical expansion of natural gas combined cycle and single cycle turbines to meet excess demand. While his approach may have the effect of slightly decreasing the system annual emissions rates it is a reasonable assumption given current market conditions. Additionally, while the AEO 2013 Reference Case shows natural gas capacity increasing by over 18 GW through 2025, coal-fired generation in the ERCOT region increases by less than 500 MW in the same period.

3.3.3.2) Load Leveling Scenarios

The “Load leveling” scenarios represent a future in which energy storage and demand response are prevalent by 2025, greatly reducing the inter-hourly and daily fluctuations in electric demand. Such a future may have significantly different generation resource usage patterns due to different operational characteristics as well as the impact of intermittent renewable energy on “net load.” As a significant demand source as well as a potential demand response and energy storage resource, EVs may play a crucial role in such a scenario and it will be important to evaluate the impact they have on system emissions.

Chart 7: Hourly January Demand in ERCOT for Base Case and Load Leveling

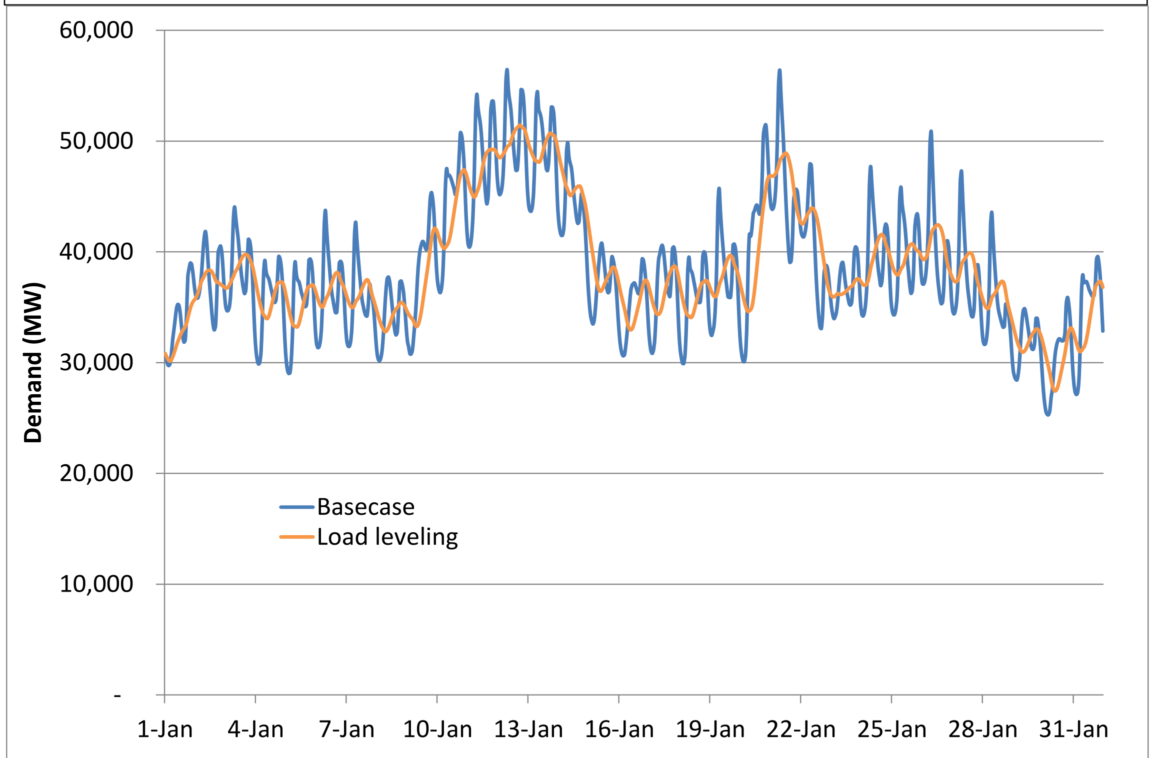


Chart 7 illustrates the change in hourly demand of the "Load-Leveling" assumptions for the month of January. This smoothing is indicative of the impact of the notional load-leveling methodology throughout the year used in this research.

Demand response and energy storage characteristics are not central to this analysis and would require a detailed simulation of operational characteristics for technology that is not widely deployed within ERCOT at this point. Consequently this analysis incorporates a simplified approach to load leveling using a simple 12-hour rolling average of demand in each scenario. For scenarios in which EV charging is modeled the 12-hour rolling average was applied to the hourly load. The effect of this process, which can be seen in Chart 7, is to reduce the "peakiness" of hourly demand within the model, a result often seen as a central goal of increased deployment of sophisticated demand management techniques using demand response and energy storage. Researchers continue to develop more sophisticated models for the use EVs in providing electric grid ancillary services and other load levelling services (Tuttle, 2012), but incorporating that ongoing work into the PLEXOS model is beyond the scope of this work. Once those models are fully developed, the methodology used in this paper for estimating the emissions impacts of those EV load-level effects is sufficiently robust to accommodate that information simply by incorporating the impact to EV charging from those models.

3.3.3.3) Low Carbon Future Scenarios

The change in generation portfolio assumed in the LCF scenarios is driven primarily by ERCOT's Long-Term System Assessment (LTSA) which projects shifts in ERCOT's generation capacity over the next 20 years through production cost modeling. The LCF scenario uses the "Updated Wind Curves" scenario of the LTSA, which in addition to updating wind resource availability assumes continued renewable energy subsidies with little decline in the unsubsidized installation cost of renewables. While the assumption that renewable energy subsidies remain in place through 2025 may be overly optimistic, the unsubsidized cost for wind and solar power continues to decline (Marcacci, 2013), a factor not well reflected in ERCOT's renewable energy cost assumptions.

A key concern when considering public policy relating to the diffusion of new technologies is the impact of long-term assumptions. Most analyses of emissions associated with EVs focus on hypothetical scenarios in which a large number of EVs are powered using either today's electric infrastructure or an assumed long-term future in which it is possible to power vehicles primarily through the use of renewable energy. The LCF scenario provides a mid-term model in which EVs are charged by an electric system using a mix of renewable and conventional energy resources. This model can then be contrasted with the Base Case models to understand the impact that changes in generation mixes can have on the emissions associated with EVs. The results from these three primary scenarios may present information more relevant to policy makers in the near term since policies related to energy and transportation tend to be incremental rather than paradigmatic.

3.3.4) EV Charging Sensitivities

The EV charging sensitivities include both real-world charging patterns using Pecan Street Inc's EV charging data as well as several simulated charging approaches in order to evaluate the impact that variations in charging patterns may have on associated charging emissions. Each charging pattern is simulated for a 100% electric vehicle using the Nissan Leaf battery characteristics, and a plug-in hybrid vehicle using the Chevy Volt's characteristics. The contribution of this paper is to identify the emissions associated with the battery powered-portion of transportation using these vehicles – methods to calculate ICE fuel efficiency are well established and can be used post hoc to evaluate total vehicle emissions.

The EV charging behavior research conducted by Pecan Street Inc. includes minimal policy influence or attempt to shift charging times for customers; as a result most customer charge times in this study begin as EV owners return from work between the hours of 4:30 and 6:30pm. Several pilot programs have experimented with a variety of methods to motivate customers to charge their EVs during off-peak electric usage hours to reduce the burden on local utilities and grid managers (Freeman, Sullivan & Co., 2012). This analysis includes a scenario in which customer charging is shifted successfully to off-peak hours with no judgment as to how this is accomplished. An additional scenario assesses the relative impact on emissions of a notional 'average charging' methodology as proposed in (Kefayati & Baldick, 2012). Under these sensitivities the EV begins charging when it is plugged in, but rather than being charged at full voltage the voltage is reduced so that the charging level remains stable and based on the owner's next expected usage of the vehicle. As this analysis does not incorporate driving patterns a standard charging period from 9pm to 6 am is assumed for these sensitivities.

Chart 8: EV charging patterns for PSI pilot project

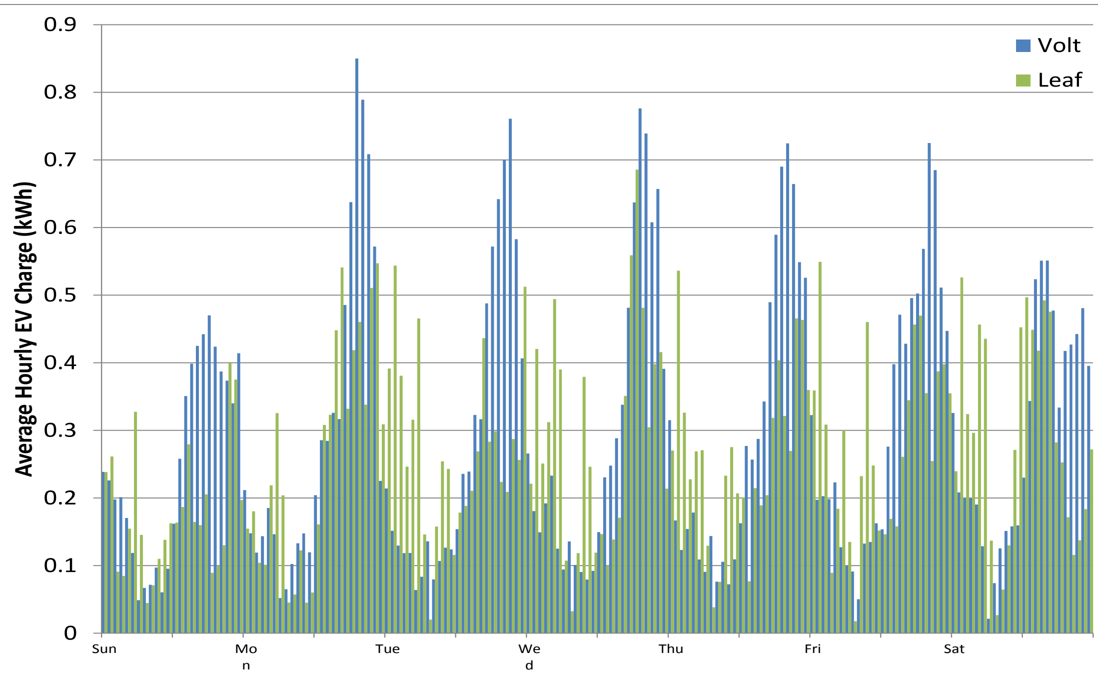


Chart 8 shows the average weekly charging patterns for Nissan Leaf and Chevy Volt owners using data from the Pecan Street Inc. pilot project.

Four primary charging patterns were used in the model: real-world charging data using the PSI data, and notional charging patterns for a standard Level 2 charger which reaches 80% of full capacity in 5 hours, a quick (4-hour) charge, and an "averaged charge. Chart 8 shows average hourly charging patterns per day of week during the fall season based on the real-world charging data. Note that the relatively low charging levels are due to the diversity of charging times. There is a clear pattern of increased charging during the evening and night-time hours, however many EV owners in the pilot project charge their vehicles during non-evening hours as well, leading to lower levels than expected during the evening and higher than expected levels during the day time. This characteristic is an important departure from the other charging strategies modeled in this research.

The standard and quick charge profiles were developed using a piece-wise linear curve with charging beginning at 10pm and maximized in the early hours with a "trickle charge" completing the battery's charge by 6am. This approach is based on an EV charging pilot developed by San Diego Gas & Electric, in which the utility used a combination of incentives and programming to ensure vehicle charging did not begin until after peak hours regardless of when the vehicle was connected to the charger (Freeman, Sullivan & Co., 2012). "Averaged charging" was developed assuming a fully depleted vehicle is connected to its charger at 9pm and disconnected at 6am; assuming a total battery capacity of 16 kWh for the Volt and 24 kWh for the Leaf, the charge rate necessary to completely fill the battery was then averaged across this time span. Chart 9 shows the daily profile of these charging scenarios, each assuming the battery is fully depleted upon connection and must be fully charged within the allotted time.

Chart 9. EV Charging simulation curves

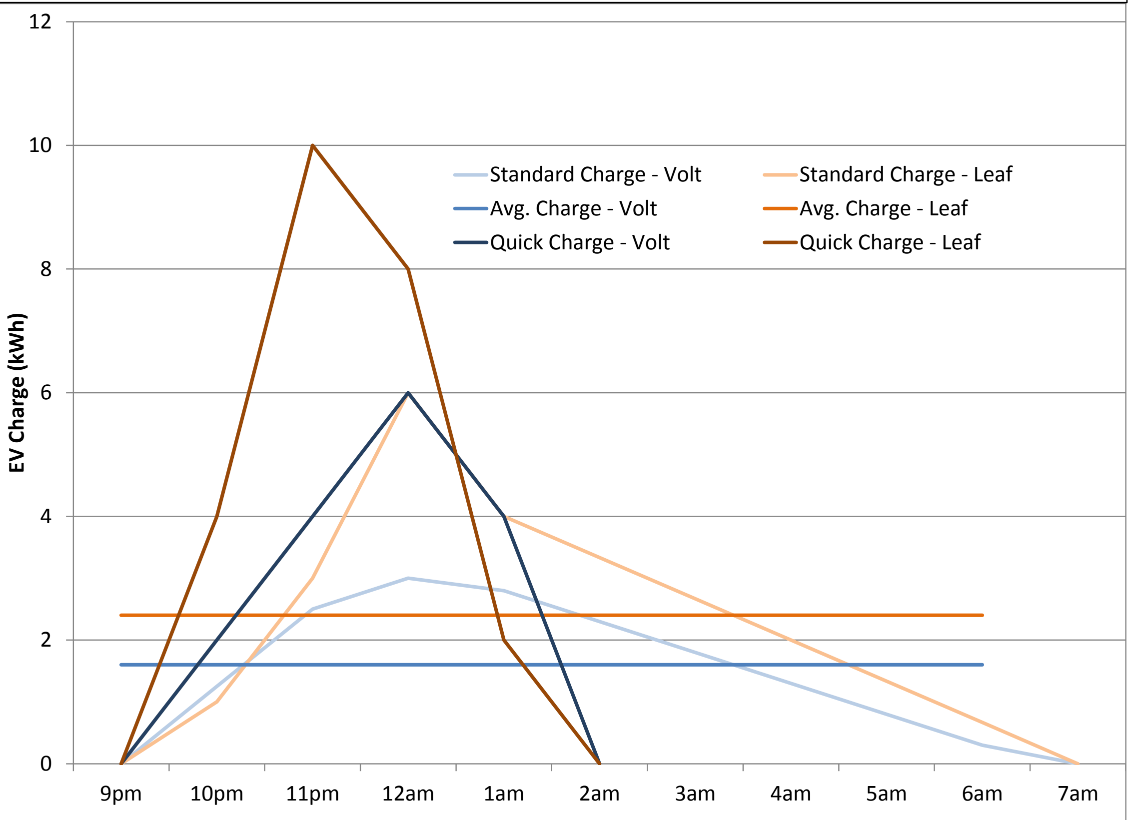


Chart 9 shows the hourly variations in charging patterns for different charging strategies and vehicles

Sensitivities for all charging strategies were calculated for both Volt and Leaf charging in the Base Case scenario. In the Load Leveling and Low Carbon Future Scenarios, sensitivities were calculated only for Volt charging needs. As the primary difference between the two vehicles is battery size, the model results for LL and LCF scenarios can be viewed as applicable to the Nissan Leaf simply at a greater magnitude.

The Nissan Leaf does have a slightly greater mileage per kWh than the Volt, which should be taken into account when applying results for the Volt to the Leaf.

3.3.5) CAFE Standards as an ICE Efficiency Benchmark

It is necessary to develop a set of assumptions for ICE efficiency in 2025 in order to compare the model results to the counterfactual in which a contemporary ICE vehicle is used. This baseline is necessary to evaluate both mpg equivalence and overall societal impact. Two ICE mpg levels are used in this analysis, both above today's light duty fleet average fuel efficiency. The 30 mpg scenario represents what is likely to be a low level of ICE fuel efficiency in 2025 while the 54.5 mpg scenario, based on the 2025 CAFE standard, represents a "best case" scenario for ICE fuel efficiency.

While it serves as a useful "best case" assumption several complicating factors arise from the use of the CAFE standard in this analysis; first the sale of EVs will be used in calculating a manufacturer's CAFE, as a result EVs are expected to play a significant role in meeting the 54.5 mpg standard (Bastani, Heywood, & Hope, 2012). The inclusion of EVs in a manufacturer's fleetwide fuel efficiency calculation could lead to a scenario in which EVs that are calculated to have a 100 mpg fuel efficiency by the EPA may account for a significant portion of the above average fleet efficiency in 2025, while ICE vehicles might remain below the 54.5 mpg standard. Using a stochastic modeling approach to determine the likelihood of meeting the 2025 standards, researchers at MIT found that under a "plausible-ambitious" scenario there is a 4% chance that average fuel economy for passenger cars will exceed 44 mpg (Bastani, Heywood, & Hope, 2012).

Further complicating the use of CAFE standards is the disconnect between fuel economy as calculated to meet the standard and actual, on-road fuel efficiency. The methodology to estimate fuel economy for the purpose of meeting CAFE standards was developed 40 years ago and has not been changed to reflect new vehicle characteristics such as air conditioning and increased acceleration. In 2011, the EPA began using a more rigorous set of tests to determine "window sticker" efficiency and while these tests may not be comprehensive they are believed to more accurately reflect fuel efficiency under modern driving conditions. As a result, CAFE based estimates of fuel efficiency are on average 28% higher than the EPA "window sticker" estimates. This discrepancy between standards means that the actual expected fuel economy, and resulting emissions from driving an ICE in 2025 may be best estimated at 36.6 mpg (UCS, 2011). The most recent CAFE standards were published jointly by the EPA and the National Highway Traffic Safety Administration (NHTSA) and include new standards regulating the CO_2 content of transportation fuel, leading the standard to achieve a 54.5 mpgCO_2 equivalent (National Academies, 2013).

3.3.6) Evaluating Emissions Impacts of EV Charging

To estimate the emissions impact of the sensitivities this analysis uses the "Fuel Offtake" output from the model, multiplied by the fuel consumption based emission rates developed using the CEMS database to arrive at a total annual CO_2, SO_2, and NO_x emissions values for each EV charging sensitivity. The relevant emissions values from the Base Case scenario were subtracted from these amounts to establish the amount of additional emissions resulting from electric vehicle charging in each sensitivity. This value was then divided by the total additional energy consumed as a result of EV charging throughout the year, arriving at a lbs/MWh emission rate for EV charging in each sensitivity, as shown below, using CO_2 as an example:

$$\textit{Total System Emissions} = \sum[\textit{Fuel Offtake}_n(\textit{mmBTu})^*CO_{2n}(\textit{lbs/mmBTu})] \qquad (9)$$

$$\textit{Emissions from EV Charging} = \sum \textit{Emissions}_{\textit{sensitivity}} - \sum \textit{Emissions}_{\textit{base case}} \qquad (10)$$

$$\textit{Emission Rate for EV Charging} = \frac{\textit{Emissions from EV Charging}}{\textit{Additional Energy use from EV Charging}} \qquad (11)$$

After this initial process for each scenario, the analysis uses existing data to develop efficiency estimate for the Volt and Leaf, in order to finally arrive at an "mpg_{ghg}" value as discussed in the UCS paper. Efficiency estimates for both vehicles are based on the vehicle's maximum state of charge (SOC) and the amount of miles estimated per charge; this approach results in a "mi/kWh" value that is useful for the final calculation. To complete this analysis a "lb per gallon" estimate is created using the EPA's value of 71.35 kg of CO_2 per mmbtu of gasoline combusted (EPA, 2013c), or 19.7 lbs of CO_2 per gallon of gasoline combusted. The estimates for SO_2 and NO_x are based on the EPA's proposed Tier 3 emissions regulations for new vehicles in 2025 (EPA, 2013a).

The impact of SO_2 and NO_x emissions are dependent both on the time and location of emission source; in general ICE vehicle emissions occur during the daytime at groundlevel and are concentrated in densely populated areas which may bear some impacts of locally emitted SO_2 and NO_x. Emissions from electric generation can occur within, nearby or at a substantial distance from densely populated areas, at an elevated height (from the smokestack), and at times that are dictated by charging behaviors. SO_2

and NO_x emitted at a substantial distance from high populations may reduce public health impacts if populations are not downwind from the point of emission. Such considerations are important to take into account in this analysis, and further inquiry is warranted relating to the potential impact to populations of SO_2 and NO_x emissions resulting from EV charging. A detailed analysis of these impacts requires detailed photochemical and geospatial modeling and is beyond the scope of this paper, however these results may provide useful insight to such inquiries (Thompson, King, Allen, & Webber, 2011), (Thompson, Webber, & Allen, 2009).

The process for calculating mpg equivalence is laid out in the formulas below using CO_2 as an example, the process changes little for each pollutant:

$$lbs\mathrm{CO_2}\ per\ mile = \frac{Emissions\ rate\ for\ EV\ Charging}{(1000 * EV\ miles\ per\ kWh)}$$

$$mpg\mathrm{CO_2} = \frac{19.7\ lbs\ per\ gallon}{lbs\ per\ mile}$$

3.3.7) Important notes regarding the 2011 model year

The model year used in the analysis presents some concerns that should be considered while reviewing results from this research. The selected year, 2011 represents the most recent year for which all necessary data are available from all three critical sets: 1) in the PLEXOS model of the ERCOT marketplace, including generation, ancillary services and pricing data from ERCOT, 2) emissions and fuel use data from the EPA, and 3) supporting data from the EIA.

Extreme weather events that occurred in 2011 might influence model results, however since all scenarios incorporate those extremes, it is not clear how these extremes will impact scenario comparisons. On February 2, 2011 continued extreme lows coupled with equipment failures across the ERCOT region led system operators to issue a Level 3 Energy Emergency Alert leading to controlled, rotating outages to avoid a system-wide outage (Doggett, 2011). From the months of June through August Texas experienced the hottest three months in the U.S. since temperature records began (Nielsen-Gammon, 2011). This extreme weather led ERCOT to declare several Level 1 Energy Emergency Alerts in which ERCOT issues public requests for conservation throughout the summer, particularly during August when conservation requests were issued during 8 days.

The weather extremes of 2011 result in extreme winter and summer weather events being modeled in this analysis, which may lead to some distortion of results. However, since ultimately the analysis is a comparative process that contrasts one scenario with such extreme weather against another scenario with the same conditions, the impacts are likely to be minimal and the potential for such impacts are noted where relevant. In addition to extreme weather, as noted in the discussion on the LCF scenarios, 2011 lacks data for meaningful coastal wind generation or ERCOT solar generation. Future analyses using this approach may be improved by focusing on 2012 or 2013 data if possible; although those years also represent hotter than average years in Texas overall they are likely more representative of historically average weather combined with contemporary system infrastructure and market conditions.

4) Modeling Results

The research in this paper presents non-obvious results that contribute to the literature on emissions associated with renewable energy and EV usage. Key results include the level of secondary emissions associated with renewable energy usage, the resulting impact of secondary emissions on the net emissions impact of renewable energy, and the impact of EV charging on system emissions under a variety of scenarios. The model behavior was generally consistent with expectations for the impact of EV charging and provided useful insights into the impacts of charging behavior and bulk power grid characteristics on the emissions associated with EV charging. While model results were consistent with expectations, it was necessary to make adjustments to model results in certain circumstances. These different outcomes and adjustments are explained in greater detail below.

4.1) Summary of the Impacts of Increased Wind Generation on System Emissions

This analysis quantitatively examines wind energy's impact on emissions from fossil fueled EGUs, finding that on a system-wide level secondary emissions due to wind variability has a minimal impact on emission rates.Secondary effects related to efficiencies and optimal scrubber performance do cause the emissions reductions to be slightly lower than would have been anticipated by assuming a complete offset of fossil fuel emissions resulting from wind EGU output (Chart 10).

Extending the renewable energy emissions impact analysis further by looking into the secondary effects of fossil EGUs ramping to follow wind fluctuations, only 99.992%, 99.995%, and 99.96% of the emissions reductions expected for CO_2, NO_x and SO_2 are achieved respectively. This secondary effect is too small to be considered statistically significant (at least for the uncertainties with this work), however the lack of statistical significance may be due primarily to the difficulty in assessing the impacts of net load on system and individual EGU emission rates.

Chart 10. Primary vs. Secondary Emissions Impact of Wind Energy in ERCOT

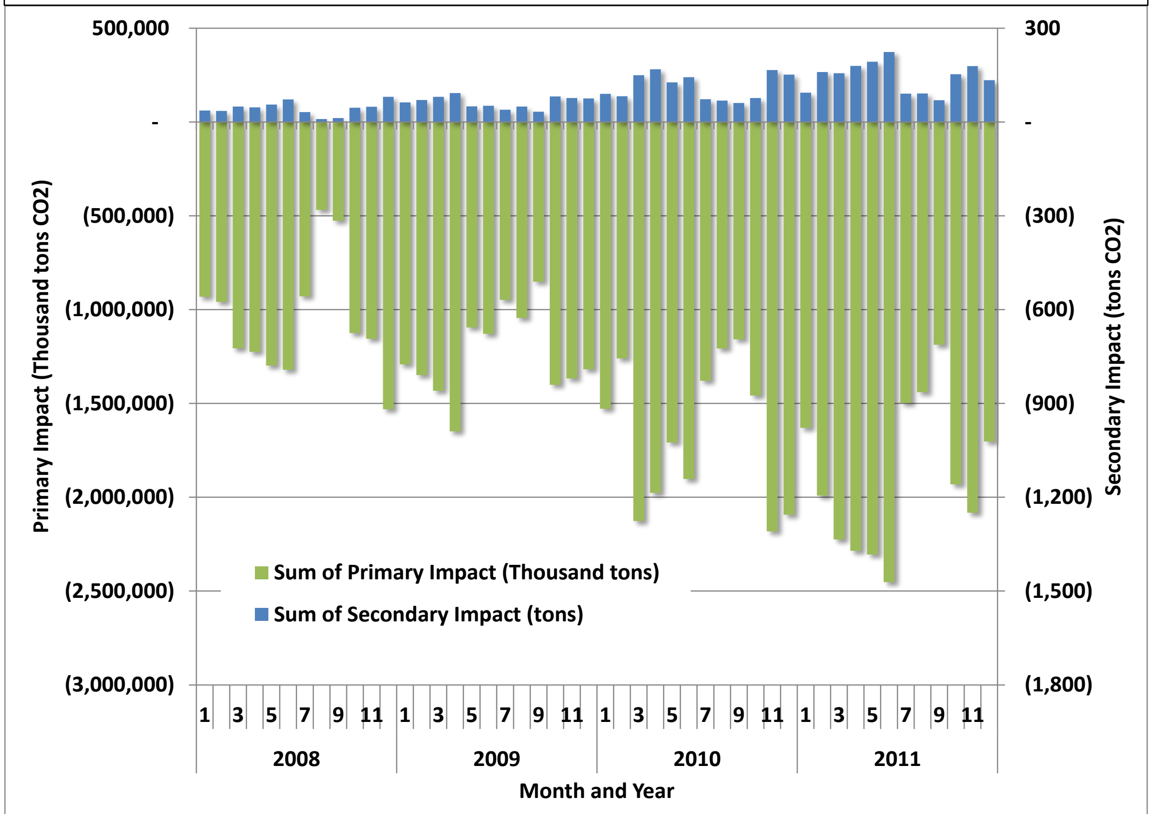


Chart 10 shows the total monthly impact of both primary and secondary emissions associated with wind. Primary emissions indicated emission reductions resulting from wind EGUs offsetting fossil fuel generation on the system. Secondary emissions represent increased emissions due to fossil fuel cycling attributable to wind EGU variability. IMPORTANT NOTE: The y-axis for Primary Impact (on the left) is in thousands of tons of CO_2 while the y-axis for Secondary emissions (on the right) is in tons of CO_2. Total emission reductions are several orders of magnitude greater than emissions increases associated with cycling due to wind energy variability.

Using both a granular calculation of emission rates and incorporating the secondary effect of wind, the total emissions from 2008-2011 in the ERCOT system were

996.5 MMT of CO_2, 0.528 MMT of NO_x, and 1.87 MMT of SO_2. Without wind power our results indicate that the emissions would be 1,070 MMT of CO_2, 0.564 MMT of NO_x,

Chart 11: Average System CO_2 Emission Rates Without Wind Generation

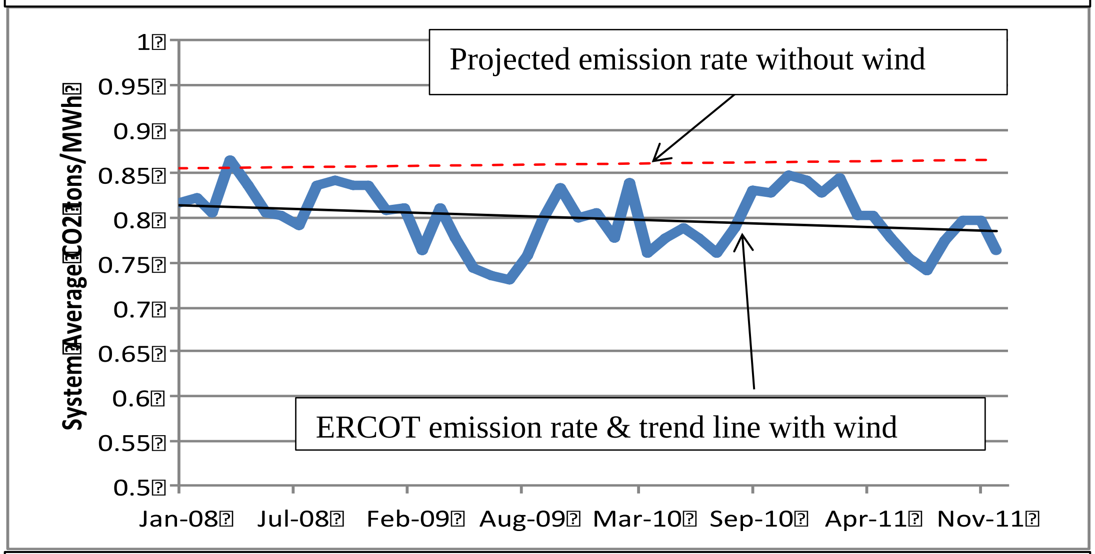


Chart 11: CO_2 emission rates would be higher in ERCOT without wind generation contributing to total system output.

and 2.0 MMT of SO_2. This impact can be seen in Chart 11 where the red line represents what the average system emission rates would be without wind generation in ERCOT. This analysis assumes that replacement generation would have a similar emission rate to ERCOT's current non-wind generation emission rate.

The approach used in this research models the secondary effect of wind energy through its impact on net load, in order to capture the total net impact of wind variability in a dynamic systemand apply that factor to the use of renewable energy to fuel electric vehicles.

4.2) Summary of the Impacts of EV Charging on System Emissions

Results for the PLEXOS simulation scenarios and sensitivities demonstrate that certain charging strategies significantly improve the vehicles mpg equivalence across pollutants, they also demonstrate that emission reductions from EV usage are possible for CO_2 and NO_x using today's electric generation infrastructure in Texas.

Table 2. Scenarios and Sensitivities Modeled

	Base Case	Load Leveling	Low Carbon Future
Base Case	EVBC	LLBC	LCFBC
PSI Charging Data - Volt	EVPSIV	LLPSIV	LCFPSIV
Standard Charging - Volt	EVSV	LLSV	LCFSV
Quick Charging - Volt	EVQV	LLQV	LCFQV
Averaged Charging - Volt	EVAV	LLAV	LCFAV
PSI Charging Data - Leaf	EVPSIL		
Standard Charging - Leaf	EVSL		
Quick Charging - Leaf	EVQL		
Averaged Charging - Leaf	EVAL		

Table 2 shows the abbreviations used to identify the scenarios discussed throughout this paper

Table 2 is reproduced here to serve as a key to the results discussed in this chapter. The PLEXOS results indicate that future market conditions such as increases in low carbon generation, energy storage, and demand response play a significant role in the mpg equivalence for EVs. In the case of CO_2 and NO_x, EV usage clearly reduces emissions relative to today's ICE vehicle fleet, which averages 24 mpg (EPA, 2013e).

These results also demonstrate the importance of EV efficiency: across sensitivities the Leaf has a higher mpg equivalent than the Volt, due to a slightly higher mile per kWh efficiency rate. Finally, as EVs are a new commercially available product and the model is set in 2025, future Corporate Average Fuel Economy standards should be taken into account. Current regulations increase fleet-wide fuel economy to 54.5 mpg by 2025; using this comparison all charging strategies are at or above parity for CO_2 emissions, while only the AV and PSIL sensitivities reach a comparable level of NO_x emissions to that expected from an ICE in 2025.

Variations in mpg equivalence in the Load Leveling scenario are muted among sensitivities due to the nature of the rolling average methodology used; however average EV mpg equivalence is slightly higher in the Load Leveling scenario than in the Base Case Scenario. Results from the LCF set of scenarios are slightly counterintuitive when viewed in the context of mpg equivalence. Namely, under this scenario, coal units are more often the marginal unit, particularly during EV charging times. That means EV charging in a low-carbon scenario actually causes emissions to marginally increases. Since wind and solar energy have negligible marginal costs they are essentially price takers, resulting in the curtailment of coal and even nuclear output in some scenarios. The curtailment of nuclear in some LCF scenarios indicates a need for further model

Table 3: MPG Equivalence Summary by Charging Scenario and Pollutant

Sensitivity	mpg_{co2}	mpg_{noX}	mpg_{so2}
EVAV	54	36	0.4
EVSV	55	39	0.4
EVQV	64	49	1.1
EVPSI	65	44	1.1
EVAL	58	38	0.4
EVSL	52	38	0.4
EVQL	72	53	1.2
EVPSIL	69	48	0.9
LLAV	61	44	0.7
LLPSIV	65	46	1.4
LLQV	62	46	0.8
LLSV	61	45	0.7
LCFAV	43	24	0.2
LCFSV	50	25	0.2
LCFQV	45	25	0.2
LCFPSI	52	26	0.2

refinement to more accurately reflect the expected outcome in which wind is curtailed as opposed to nuclear output due to constraints on nuclear curtailment capabilities.

While SO_2 emissions likely increase as a result of EV charging, the societal benefit of reduced NO_x and CO_2 emissions is several orders of magnitude greater than the social cost of the slight increase in SO_2 emissions our results indicate. On an individual EV basis, overall social cost is reduced relative to a 30 mpg vehicle in all sensitivities, due largely to the social benefit of reduced CO_2 emissions (Chart 12).

Chart 12. Societal Impact of EV Charging as a Replacement for 30 mpg ICE Usage

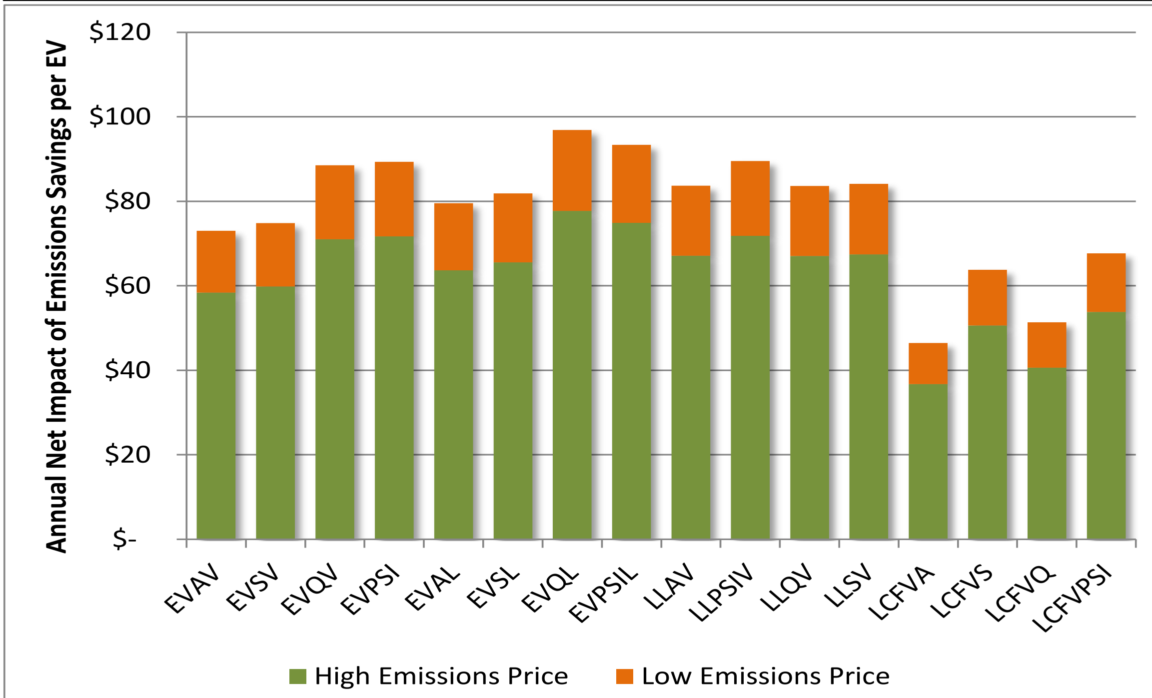


Chart 12. EV charging results show an annual net societal benefit resulting from individual EV usage displacing a 30 mpg ICE vehicle under any charging strategy for both low and high emission price conditions.

4.3) Detailed Emissions Analysis Results - Impacts of Renewable Energy on Fossil Fuel Emissions

4.3.1) Regression Results: Correlations Between Net Load and Emission Rates

As discussed in chapter 3, this research utilizes a two-step regression analysis process to identify correlations between wind EGU variability, and fossil fuel EGU emission rates. In general, the CO_2 regression models had the closest fit across fuel types (coal, natural gas, all fossil fueled generation) as shown in Table 3 below. The closer fit indicates that this model is most effective at predicting CO_2 emissions as a result of the combined exogenous factors in equation 4 relative to NO_x and SO_2 emissions which exhibit poor model fit. As noted earlier, this better fit for CO_2 is likely due to the fact that CO_2 emissions are currently uncontrolled in the U.S. and thus should more closely track fossil-fueled EGU output while NO_x and SO_2 emissions are often controlled resulting in a potentially non-correlated relationship with EGU output. Likewise the full system model which uses data from all fuel types (including non-coal and non-natural gas) exhibited the best fit, with natural gas showing the next best fit and coal EGUs showing a relatively poor fit for the model.

Table 4 below shows modeling results for adjusted R square and correlation coefficients for key independent variables, the table includes results for models including all fossil fuels as well as models disaggregated by coal and natural gas fuel type. The correlation coefficients for each independent variable indicate the degree to which the variable impacts model emissions both in scale and direction. While coefficients for CO_2 emissions are small relative to typical emission rates, typical NO_x and SO_2 emission rates are much lower, thus the relative significance of the coefficients is increased for those pollutants, indicating a higher sensitivity to changes in net load.

Table 4: Equation 4 Results

	All Fossil Fuels			Natural Gas EGUs		
Independent Variable	CO2 tons/MWh	Nox lbs/MWh	SO2 lbs/MWh	CO2 tons/MWh	Nox lbs/MWh	SO2 lbs/MWh
Adjusted R Square	0.8204	0.5941	0.7157	0.5884	0.53	0.4878
γ	-1.16E-05	-6.03E-06	-1.80E-04	-1.08E-06	4.44E-05	-4.63E-05
Δγ	6.50E-06	2.14E-05	1.85E-04	-2.96E-07	-2.45E-05	5.27E-05
Δγ^2	-1.32E-10	-7.39E-10	-2.42E-08	4.18E-09	5.17E-09	-2.42E-09
system heat rate	1.10E-04	2.84E-04	7.24E-04	1.20E-04	1.75E-04	2.98E-04

	Coal EGUs		
Independent Variable	CO2 tons/MWh	Nox lbs/MWh	SO2 lbs/MWh
Adjusted R Square	0.4755	0.2796	0.2358
γ	-1.69E-07	-1.66E-05	-9.63E-05
Δγ	1.14E-06	3.28E-05	2.14E-04
Δγ^2	3.70E-10	4.51E-09	-5.81E-09
system heat rate	3.07E-05	1.79E-04	6.07E-04

Table 4: Regression analysis results from equation 4, showing model fit and correlations coefficients for key independent variables. The results show a relatively good fit (“Adjusted R Square) for the CO_2 “All Fossil Fuels” model. Directionality of independent variables in the CO_2 “All Fossil Fuels” model show that increasing γ correlates with lower emission rates, while increasing Δγ correlates with lower emission rates.

These results conform with prior analyses, most often using data from periods with higher natural gas prices, which conclude that natural gas is most often on the margin in the ERCOT market and thus most likely to be impacted by changes in net load. There is some question regarding the extent to which recent low natural gas prices have affected the merit order – the order in which EGUs are selected for dispatch based on marginal cost – moving coal to the margin in some hours of the year.

These results confirm that that although low natural gas prices may have moved some coal facilities higher in the merit order stack, natural gas generation is still impacted more than coal by changes in net load. The study period includes 3 years reflecting current low prices and only one year (2008) where wellhead prices were above $5/Tcf allowing for an examination of whether current low prices have resulted in a noticable shift in the merit order. Furthermore an analysis of 2011 using the same methodology yields similar results, although with notably higher adjusted R Squares, natural gas remains a better fit (i.e. is more highly correlated) with changes in net load. In Table 4 above, increases in net load lead to decreased emission rates across all fuel types with the exception of natural gas NO_x emission rates. The impact of net load on natural gas NO_x emissions indicates that natural gas units that are higher in the supply stack, and thus run less frequently, have higher NO_x emission rates than natural gas EGUs that are run more often. EPA's Air Markets Program Data (Chart 13) shows that a substantially greater number of outliers with high NO_x rates exist in the population of plants with lower capacity factors (i.e. less operating time per year), specifically below 20%.

Chart 13. NO_x Rates for EGUs by Capacity Factor

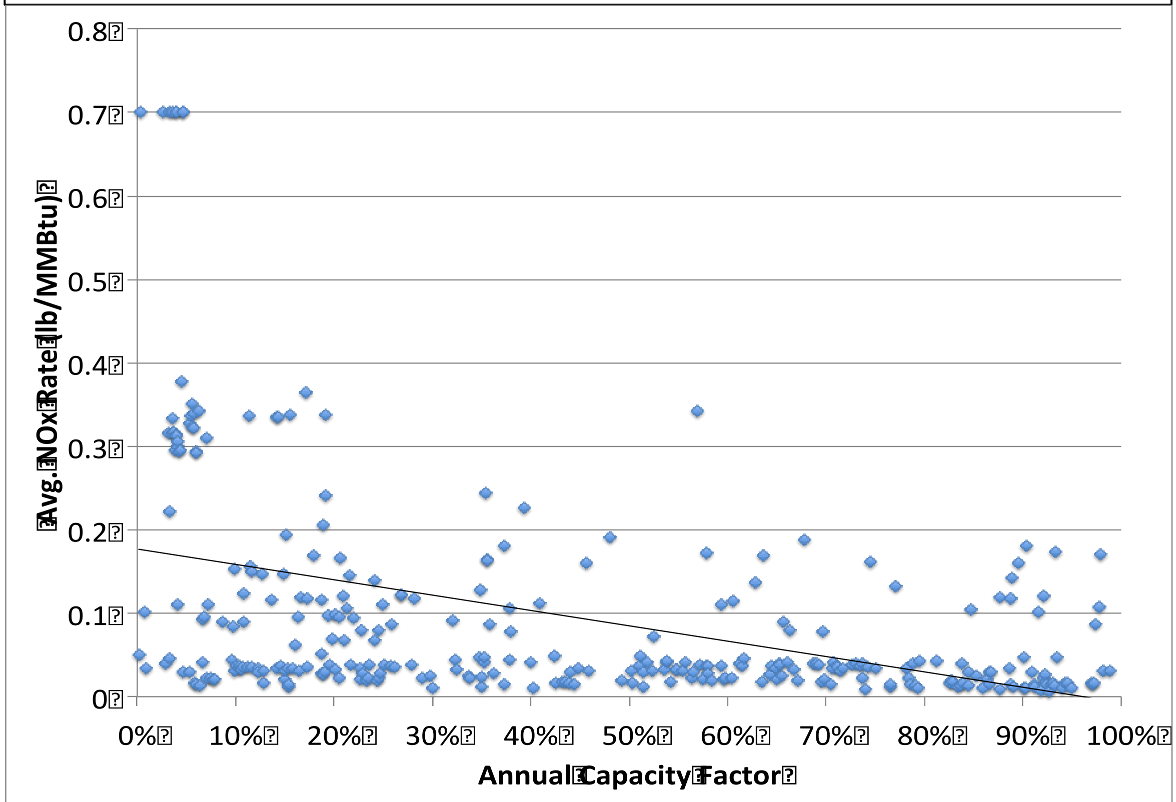


Chart 13: As EGU capacity factors decrease emissions increase, indicating higher NO_x emission rates for peaking EGUs.

While the impact of total net load on emissions is relatively uniform across all instances except natural gas NO_x emissions, $\Delta\gamma$ and $\Delta\gamma^2$ show that changes in net load have varying impacts on system, natural gas and coal EGU emission rates respectively. Specifically increases in $\Delta\gamma$ appear to increase emission rates, indicating that EGU inefficiencies induced by ramping may lead to increased emissions intensity, although the correlation coefficient is small enough to be negligible. In this context CO_2 and NO_x emissions from natural gas EGUs stand out as being negatively correlated with $\Delta\gamma$ possibly resulting from a combination of natural gas EGU's greater ramping flexibility and the fact that both CO_2 and NO_x are uncontrolled in many of the natural gas EGUs presumed to be adjusted to meet intra-interval net load needs (Charts 14 and 15). Across all analyses the system heat rate is positively correlated with emission rates as expected.

Chart 14. Natural Gas Emission Rate Correlations with Net Load

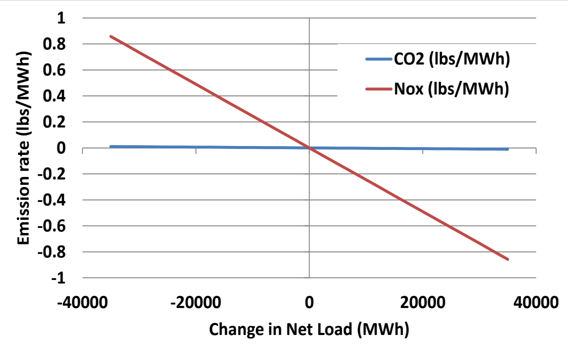
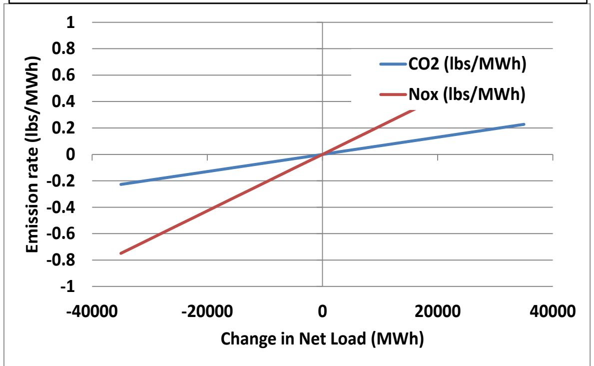


Chart 15. System Fossil Fuel Emission Rate Correlations with Net Load



Charts 14 and 15 show the difference between the natural gas and system wide emission rate correlations with net load: for natural gas, as net load decreases, emission rates increase (this increase is much smaller for CO_2). System-wide fossil fuel emission rates are positively correlated with changes in net load: as net load increases, emission rates increase.

4.3.2) Regression Results for Individual EGUs

Results using this model for individual EGUs exhibited a poor fit, indicating that the regression model used did not approximate emissions behavior for individual units well enough to draw meaningful conclusions about individual EGU behavior. However, the poor fit might simply indicate that on an individual level, broad system-wide changes in net demand are unlikely to impact individual units that might be responding to a mixture of system-wide and localized changes. To fully account for localized and economic dispatch effects it might be necessary to incorporate transmission congestion and other local as well as economic factors, but such an analysis is beyond the scope of this paper.

Table 5 shows the EGUs identified in Cullen (2011) as being frequently offset in the dispatch curve by wind energy output, and as such they are likely to see the highest level of impact to emission rates as a result of frequent ramping induced by wind EGU output. These results do not invalidate those from Cullen's analysis, rather these results can be seen as a further indicator that changes in net load, including wind EGU output do not seem to drive changes in EGU emission rates. It is possible that the supply curve has shifted to such an extent since 2007 that a different set of EGUs would be offset more frequently than the units in Table 2. The plants listed below are known to be offset either by wind directly or as a result of their place in the economic dispatch order, for instance Austin Energy has stated an operational preference for reducing output from their ownership share of Fayette 1 and 2. In September 2012, Energy Future Holdings announced plans to idle Monticello units 1 and 2 due to higher marginal costs relative to current market conditions, placing the unit in a more marginal position in the dispatch order.

Table 5. Equation 4 Results by Generating Unit

	Plant Specific CO2 Rate Impacts				
Independent Variable	Big Brown 1	Big Brown 2	Fayette 1	Fayette 2	Monticello 1
Adjusted R Square	0.03811	0.02651	0.2206	0.1068	0.0115
γ	2.11E-06	-5.36E-06	4.84E-06	1.77E-05	1.81E-05
Δγ	-2.27E-05	1.49E-05	-1.61E-05	-2.35E-05	-1.34E-05
Δγ^2	-2.19E-08	-2.47E-09	-1.77E-08	-3.19E-09	-7.71E-09
system heat rate	-3.21E-05	3.96E-05	-1.83E-04	-2.20E-05	2.68E-04

Table 5: Plant specific CO_2 rate impacts are difficult to model through this

Despite the model's weak correlation of changes in net load to emission rates for individual EGUs identified in Cullen (2011) as likely to be offset by wind, the fact that the $\Delta\gamma$ variables on a system-wide level have a minimal impact on emission rates indicates that cycling caused by changes in net load have a minimal impact on emission rates. In the individual and system-wide models, as well as the models disaggregated by fuel type the orders of magnitude for $\Delta\gamma$ correlation coefficients are between 10^{-4} and 10^{-7} across all emissions, with SO_2 emissions often having the highest correlation coefficient. Using these correlation coefficients to model the impact of $\Delta\gamma$ and $\Delta\gamma^2$, in order to incorporate both the impact of the direction and magnitude of changes in net load, emission rates range between 10^{-4} and 10^{-6} lbs (NO_x and SO_2) or tons (CO_2) per MWh. As a result it seems that changes in net load lead to little attributable emission rate increases, an important consideration in evaluating the environmental benefits associated with variable generation resources. This finding contradicts results from earlier analyses, such as the BENTEK analysis discussed earlier (BENTEK, 2010) that asserted the secondary emissions impacts from wind variability significantly reduce or in some cases overwhelm direct emissions reductions achieved by wind generation displacing fossil fuel generation.

4.3.3) Regression Results: Correlations Between Net Load and Wind Generation

In the analysis for the impact of wind generation on $\Delta\gamma$ it is only necessary to run a single model because $\Delta\gamma$ is a system-wide variable. The regression model using Equation 5 has a relatively poor fit with an adjusted R square of .57, indicating that the descriptive variables included only account for a fraction of the total $\Delta\gamma$. While it would be ideal to have a better model fit, as they stand the results are telling: to the extent that wind is included in the descriptive statistics (wind EGU output, Δwind, Δwind^2) this model demonstrates that wind is a poor indicator of $\Delta\gamma$. The strongest indicators by far are seasonal, temporal and temperature variables, all of which are likely to exhibit some multicollinearity with wind EGU output, which could in effect 'mask' the impact that wind EGU output has on Δγ.

Although it weakens the model significantly, to avoid any multicollinearity issues and attempt to reveal system impacts solely attributable to wind EGU output all possible correlated variables (time, season, temperature, etc.) were removed from the model, leaving only the wind EGU descriptive variables. Results from both approaches can be seen in Table 6; model results indicate that wind EGU output and $\Delta wind^2$ is correlated with increased $\Delta\gamma$ while increases in Δwind correlate at the highest order of magnitude of all variables with decreased $\Delta\gamma$, indicating that large changes in wind output seem to correlate with lower overall system changes in net load. This result indicates that increases in total wind output are correlated with increased changes in the system net load, as is the absolute change in wind output to a lesser degree.

Table 6: Equation 5 Results

Wind Impact on Δγ		
Independent Variable	Full Model	Wind Variables Only
Adjusted R Square	0.566	0.115
Wind EGU MWh	9.22E-03	2.98E-02
Δwind	-8.58E-01	-1.22E+00
Δwind^2	1.88E-04	6.10E-04

Table 6: Net load and wind generation correlations show a net slight increase in emission rates over time.

The relationship between Δwind and $\Delta\gamma$ illustrates that the primary impact change in wind EGU total MWh output might have is to decrease the change in net load as wind EGU output increases. This would indicate that as an example, periods in which increases in wind EGU output occur during periods when net load –including added wind output—is falling. At the same time higher wind EGU output is correlated with increases in $\Delta\gamma$; these paired results may seem counterintuitive, however further examination is helpful in understanding what the results indicate about how wind output affects the system.

Increased wind generation generally occurs at night in our dataset, leading to higher Δwind; at the same time, total load begins to fall during the same period, resulting in negative $\Delta\gamma$, hence the inverse correlation between the two. The correlation coefficient for total wind output operates in a different manner than the Δ wind variable; in this case the coefficient indicates that hours in which the system experiences high wind output, the system also experiences higher or more frequent changes in net load. The absolute change in wind output has a similar relationship, with the correlation of Δwind^2 and $\Delta\gamma$ indicating a small but relevant positive correlation with changes in net load results from increased increased absolute changes in wind output.

Combining the results from equation 4 and 5 allows for an evaluation of the secondary effect that wind EGU output has on overall system emission rates, i.e. the extent to which changes in net load attributable to wind generation impact fossil fuel generation emission rates. The equation used to estimate this impact is developed as follows:

First the amount of net load attributable to wind is calculated based on a simplified version of equation 5, identified as γ_{wind}:

$$\gamma_{wind} = \gamma(wind) = \beta_{1,wind}(wind\ MWh) + \beta_{2,wind}(\Delta wind) + \beta_{3,wind}(\Delta wind^2) \tag{6}$$

Next, inserting γ_{wind}, the change in emission rate attributable to wind (ΔE_{wind}) is calculated through wind's impact on net load:

$$\Delta E_{wind} = \beta_{1,\gamma}(\gamma_{wind}) + \beta_{2,\gamma}(\Delta\gamma_{wind}) + \beta_{3,\gamma}(\Delta\gamma_{wind}{}^2) \tag{7}$$

Substituting the values determined in equation 6 for γ_{wind} into equation 7 as γ_{wind}, $\Delta\gamma_{wind}$, and $\Delta\gamma_{wind}{}^2$ an average secondary effect of wind EGU output can be seen in Table 6 for all three pollutants analyzed, using the respective correlation coefficients for each pollutant (wind MWh, Δwind, $\Delta wind^2$, γ_{wind}, $\Delta\gamma_{wind}$, $\Delta\gamma_{wind}{}^2$). These results indicate that wind induced variability causes a slight but measurable increase in system-wide emission rates, most likely as a result of system inefficiencies introduced by wind generation variability. The critical question then, discussed below is the scale of this secondary impact of wind relative to its primary impact of offsetting fossil fueled EGU output, curbing fossil fueled emissions.

Table 7: Emission Rate Impacts of Wind Induced Variability

Δ CO_2 *(tons/MWh)*	*0.04*
Δ SO_2 *(lbs/MWh)*	*0.47*
Δ NO_x *(lbs/MWh)*	*0.16*

Table 5 shows the secondary effects of wind generation on emission rates, representing a small portion of total EGU emissions. A positive Δ indicates the secondary effect of wind EGU output increases average system emission rates for fossil fueled EGUs.

For example, if there were no wind power in the ERCOT system, existing individual fossil EGU unit emission rates would likely be slightly lower, however their usage would be higher, resulting in a substantial increase in overall system emissions.

4.3.4) The Relationship Between Marginal Emission Rates and Total System Emissions

An exclusive focus on marginal emission rates produces results that are not satisfactory for understanding pollution reduction goals and in fact can be misleading. While avoided emissions based on marginal emission rates may be useful for regulatory compliance purposes, it is also important to consider the absolute impact on emissions, particularly when considering cumulative effects over time. Direct offsets of NO_x and SO_2 have effects that are highly time-dependent, specifically the status of those pollutants as precursors to ground level ozone and particulate matter means that a key societal benefit from the reduction of their emissions occurs during specific hours. This analysis focuses on the long-term policy implications of emissions impacts, however, and a focus solely on impacts to emission rates misses the larger goal of measuring total system emission impacts.

Emissions of SO_2 and NO_x also have less time dependent societal benefits such as the reduction of acid rain, while the societal benefit of CO_2 reductions is only slightly impacted by the time of emission. As a result, a marginal emissions analysis only captures part of the societal benefit of wind EGU output while discount the impact contemporary output has on the shaping of future supply curves and thus future marginal emission rates. In a 2009 analysis the Public Utilities Commission (PUC) of Texas found that “[f]or each additional 1,000 MW of wind that was produced, the analysis showed that the clearing price in the balancing energy market fell by $2.38 per MWh” (PUCT, 2009). In the spring of 2011, wind EGU output reached an instantaneous peak of 7,599

MW (ERCOT, 2011) at 8:41p.m., which would result in a reduction in wholesale power prices of approximately $18/MWh using the PUC's methodology. While this price impact represents just one estimate, similar analyses have observed what has been termed the "merit order affect" – the reduction of wholesale power prices as a result of low energy marginal costs displacing higher marginal cost units in the merit order stack and lowering the marginal price of energy (Weigt, 2009). Over the long term these lower prices make it difficult for units that are only marginally profitable to remain operational, potentially leading to the retirement of fossil fuel generation that would have otherwise remained in operation. Coupled with a similar impact from historically low natural gas prices this might result in a changed ERCOT supply curve; although it is not certain that the resulting curve will be less carbon intensive such has been the trend during this study period (Chart 16). It is difficult to determine what role wind may have played in this

Chart 16. ERCOT CO_2 Rate Decline During Study Period

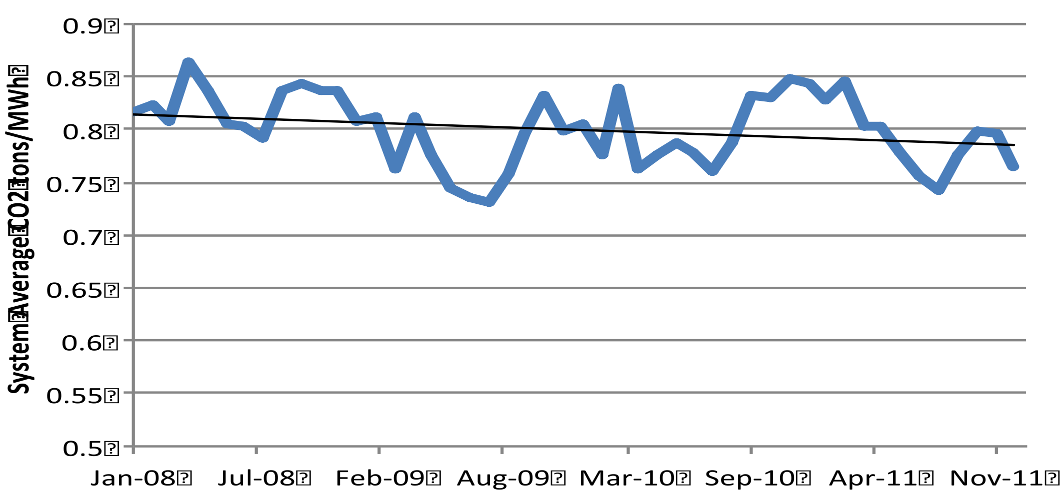


Chart 16: CO_2 rates in ERCOT have declined over time, which is consistent with the expected emission impacts from growth in wind generation over that same time period.

decline without further analysis, however it is important to note that the emissions decreased in a way that is consistent with increasing wind generation. And, the societal benefits from emission offsets related to wind EGU output may extend beyond a marginal emissions impact.

Developing a rigorous marginal emission analysis is beyond the scope of this paper, however the EPA CEMS dataset does allow for the use of hourly average system-wide emission rates to estimate total emissions offset by wind EGU output with higher fidelity than was previously analyzed. An estimation of hourly system-wide emission rates is primarily useful to better understand the scale of direct emission reductions from wind relative to the impact to fossil EGU emission rates determined through this analysis. The modeling results show a slight decrease in avoided emissions but as Chart 17 indicates, those impacts across all measured emissions are still less than 0.05%.

Chart 17: Monthly Average Secondary Emissions Impacts from Wind EGU Output

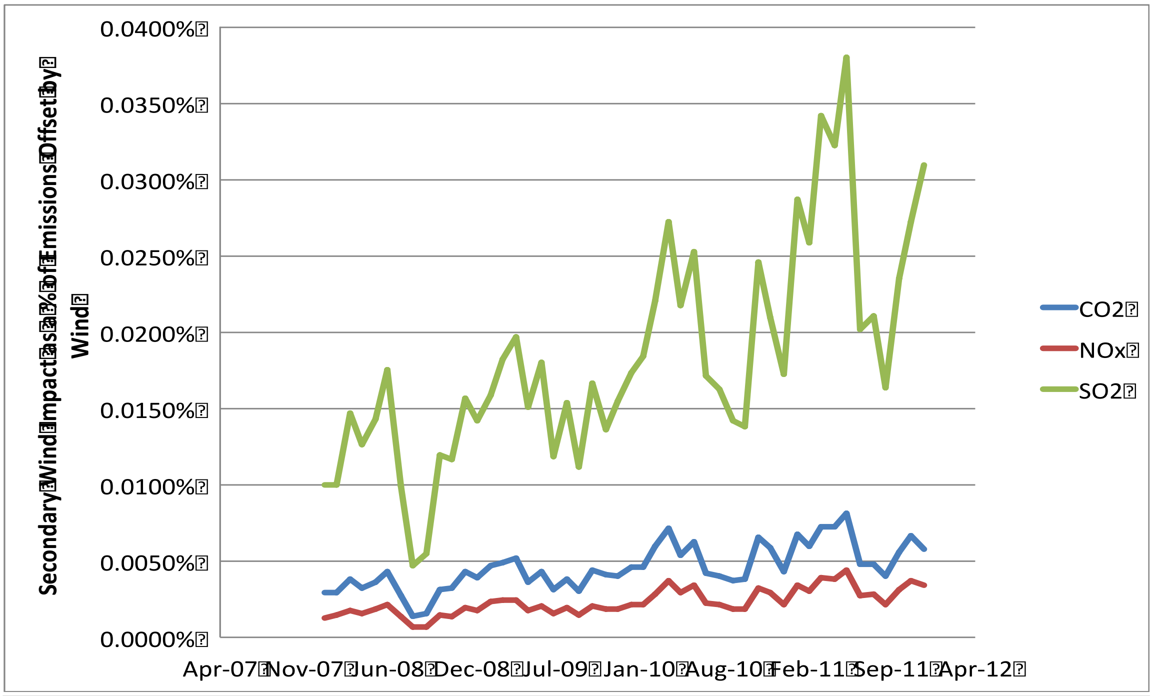


Chart 17: Average secondary emissions impacts from wind have increased over time but remain several orders of magnitude below the emissions offset by wind energy.

The small scale of this secondary impact is primarily a result on the modeled correlation coefficients from equation 4 as used in equation 7 for γ , $\Delta\gamma$ and $\Delta\gamma^2$ and overall emission rates, which have orders of magnitude at or below $1x10^{-5}$. While the correlation coefficients in equation 5 are higher orders of magnitude, giving the independent variables in that equation greater influence over γ_{wind}, as γ_{wind} is substituted into equation 7 the ultimate effects are muted. As a result these results cannot be seen as statistically significant; nevertheless they do provide some insight into the scale of the impact, as well as the gradual growth in impact over time.

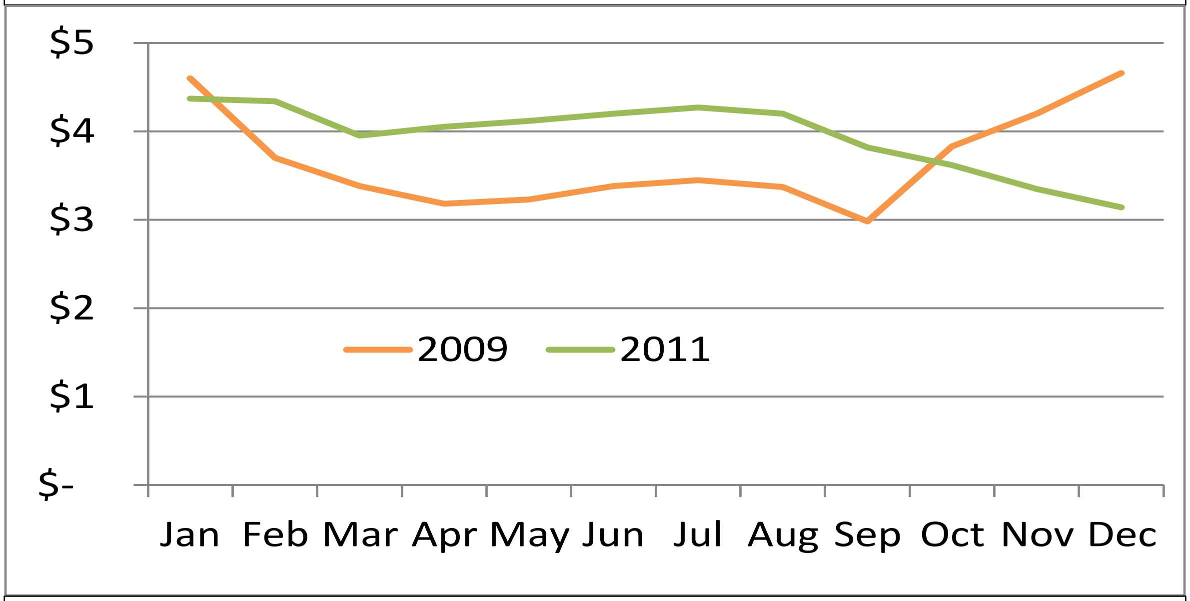
4.4) Detailed PLEXOS Charging Analysis Results Results

4.4.1) **Base Case Scenarios – Reflecting the Impact of EV Charging Using the Current ERCOT Fleet Mix**

The Base Case Scenario reflects results of an ERCOT model in 2025, with demand growing at approximately 0.8% annually and the generation fleet unchanged with the exception of additional natural gas generation to meet 2025 demand in excess of the current generation fleet's capabilities. These results show a system-wide CO_2 emission rate of 1,510 lbs/MWh, 28% higher than the 1,182 lbs/MWh emission rate estimated for the ERCOT region by the EPA in 2009 (EPA, 2012). However, in parallel, the total number of MWh generated from emitting sources changes from 372,541,440 MWh in our simulation to 337,031,900 MWh from the EPA, a 10% difference.

It is possible that the inclusion of Private Use Network generators in the PLEXOS model accounts for the entirety of the increase in emission rates relative to the EPA estimate however it is unlikely that this change alone accounts for the difference. Higher natural gas prices in 2011 relative to the EPA estimate year of 2009 may also play a role in this differential (Chart 18) by raising the marginal cost of generation for natural gas EGUs in 2011 which might cause increased coal EGU output. The difference between EPA estimates and outputs from this analysis might indicate that results from the Base Case model likely underestimate the emissions reductions achieved through EV usage as indicated by this higher emission rate, however these results remain relevant establishing both a 'lower bound' for the emissions benefits of EV usage and the relative merits of different EV charging strategies.

Chart 18: Historical Wellhead Natural Gas Prices



Source: Energy Information Administration, "U.S. Natural Gas Prices"

Generation output patterns change as expected with the introduction of EV charging, specifically output from both coal and natural gas generation is increased; since wind generation is generally a 'price-taker' in the ERCOT market, it generates at available capacity and is not affected across scenarios which model a single year. During high levels of wind coincident with low load levels, there may be a need to curtail wind output; however such a situation did not arise in our analysis. The charts below show the relationship between EV charging on system demand, and generator response throughout a sample day.

Chart 19. Impact of EV Charging on System Demand for an Average Tuesday in July

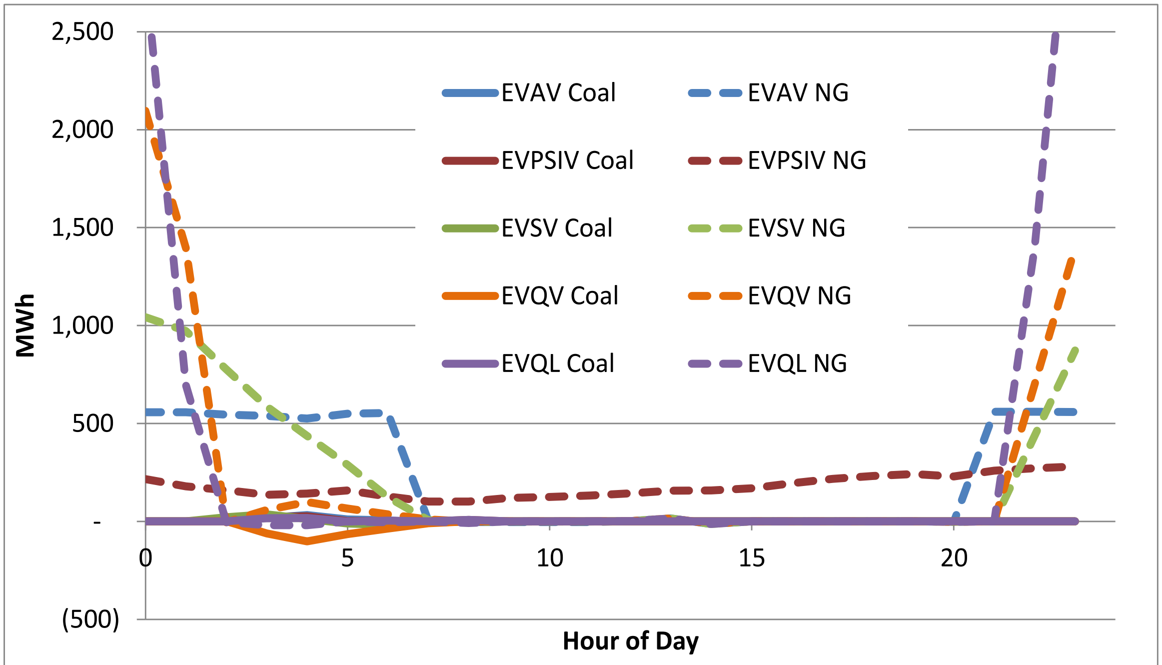
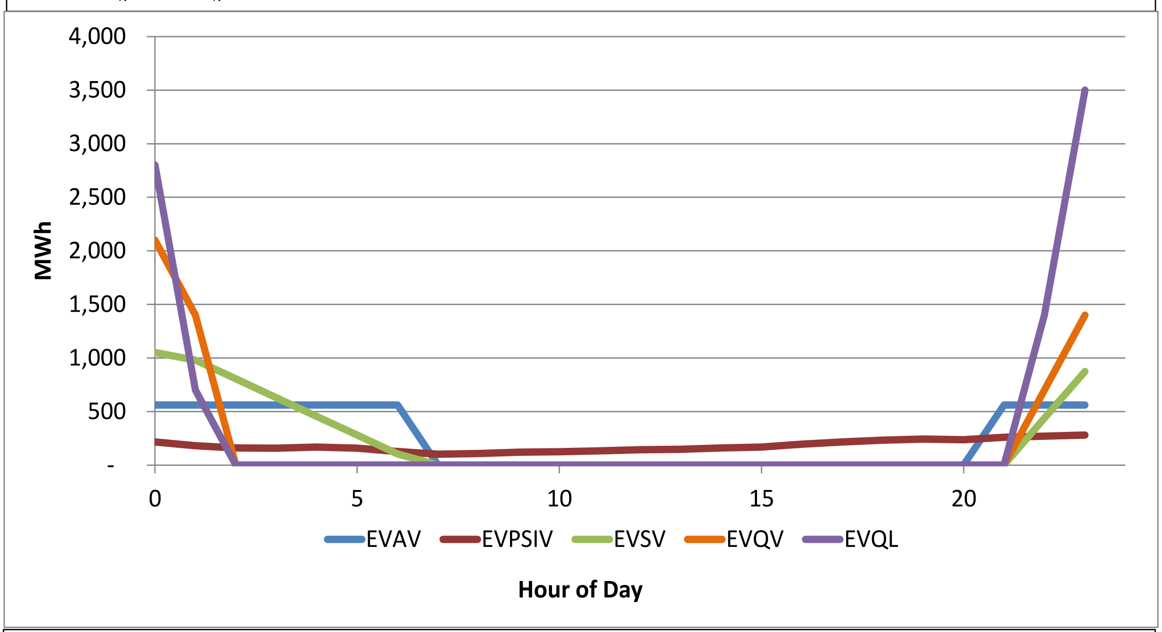


Chart 20. Impact of EV Charging on Generator Output in ERCOT for an Average Tuesday in July



Charts 19 and 20 above illustrate the impact that different EV charging patterns have on EGU output in the summer by fuel type and in total respectively. The charts show that during a summer weekday the increase in demand, mostly at night, is met almost entirely by natural gas generation. The slight reduction in coal output form the Quick Volt charging scenario relative to the base case is matched by an increase in natural gas generation output. The Quick Leaf scenario is included to reflect the impact of the highest level of charging modeled.

Chart 21. Impact of EV Charging on Generator Output for an Average Monday in November

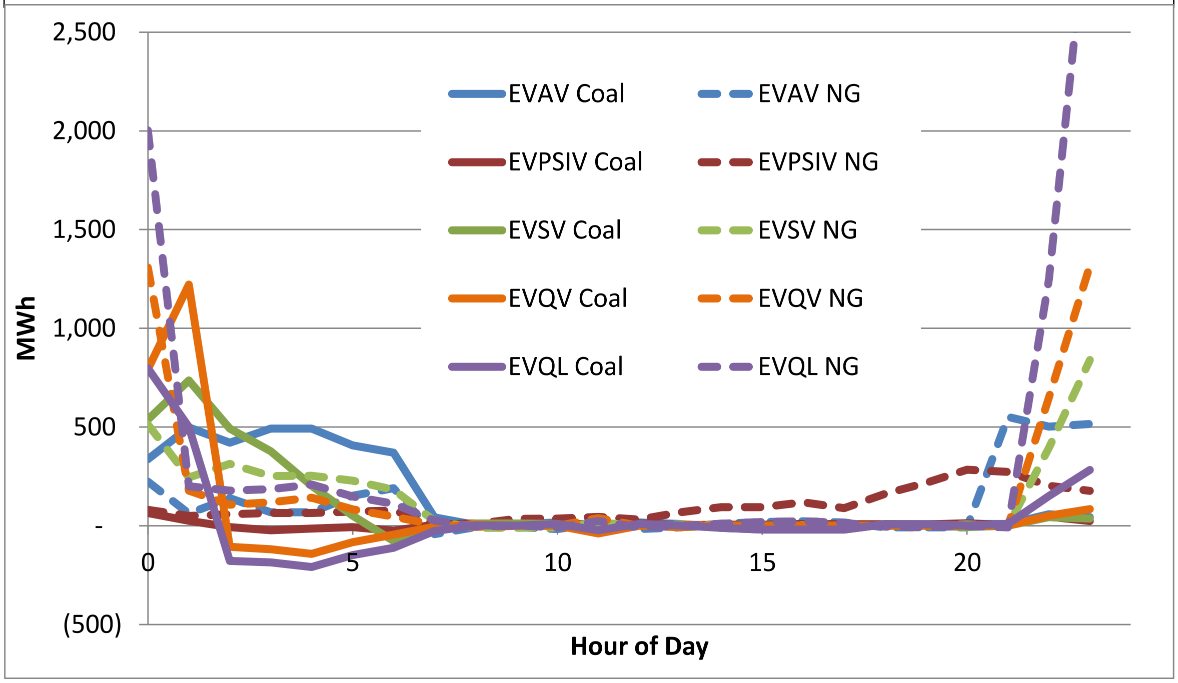
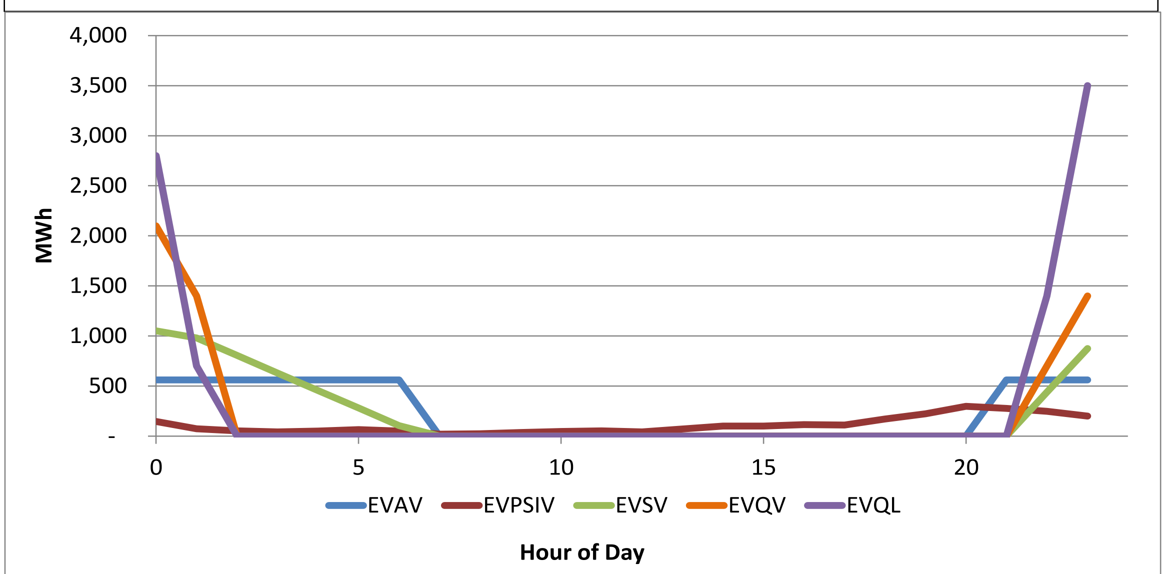


Chart 22. Impact of EV Charging on System Demand for an Average Monday in



Charts 21 and 22 above illustrate the impact that different EV charging patterns have on EGU output in the winter by fuel type and in total respectively. The charts show that during a winter weekday the increase in demand, mostly at night, is met through a mix of natural gas and coal generation. In the quick charging scenarios during this season, natural gas output is higher to meet initial increased demand, with higher coal output during later hours of the charging period and some reduction in coal output as charging reduces over time.

As the charts above indicate, the model results show a seasonal shift in the source of electricity used to meet additional demand from EV charging; generally during the summer baseload coal facilities run at maximum capacity to capture higher summer wholesale prices. As a result it is unlikely that summer charging would lead to increased coal generation, a result the model bears out. Instead during the summer, increased demand is met primarily through increased natural gas generation. During the winter coal plants experience more varied output throughout the day and season, as a result increased demand from EV charging is met through a mix of increased coal and natural gas generation output. This seasonal shift in generator output is important in the consideration of pollutants for which time of year is important, such as SO_2 and especially NO_x, where emissions during the summer contribute to increased ground level ozone and associated negative health impacts.

The sensitivity results indicate that natural gas accounts for between 68% and 88% of increased generation output used to meet additional demand, with natural gas in the quick charging scenarios for both the Leaf and Volt accounting for 86% and 76% of the increased output respectively. In addition to the variety in fuel source increases, the technology makeup of increased natural gas generation varies among scenarios (Chart 23). Natural gas fueled EGUs are broken up into three primary categories based on the generator used (natural gas boiler, open-cycle gas turbine, and combined cycle gas turbine); both fuel type and technology type impact overall emissions impacts of different charging strategies. A key determinant of a high mpgCO_2 appears to be the ratio of additional demand met by coal to that met by combined cycle natural gas. As a result of

Chart 23: Increased Generation by Technology Type Relative to Base Case Scenario

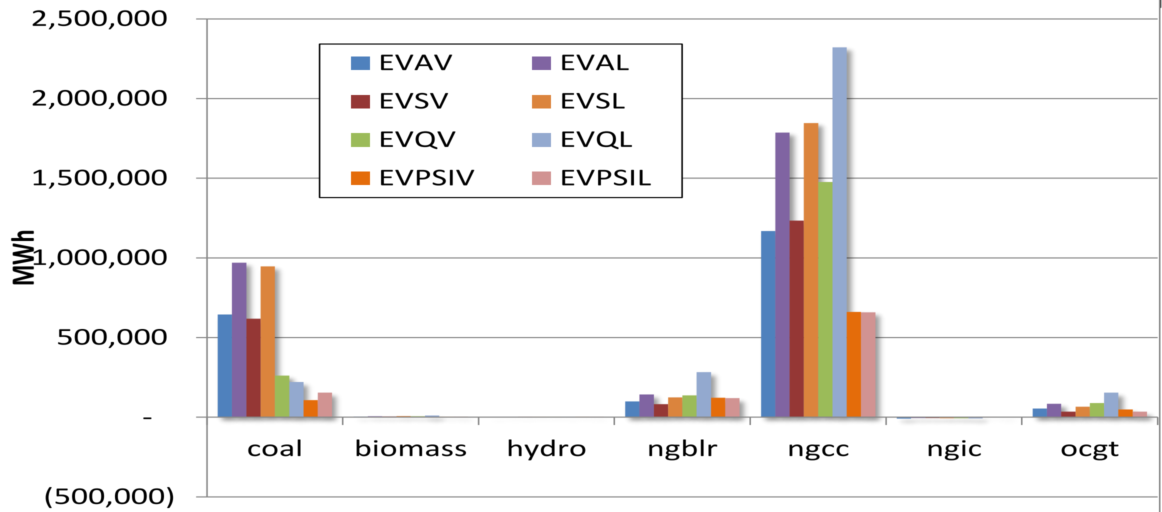


Chart 23 shows the increased generation by technology type for each sensitivity relative to the Base Case. The ratio of coal to natural gas use impacts the emission benefit for each charging strategy, as does the ratio of natural gas CC use to other natural gas generation technologies which typically have higher emission rates. The X-axis represents different generation technology types: ngblr, ngcc, ngic, and ocgt represent natural gas boiler, natural gas combined cycle, natural gas internal combustion, and open-cycle gas turbine generators respectively.

these differences, the EVPSIV sensitivity has a slightly higher mpgCO_2 than the EVQV sensitivity, largely due to a relatively higher portion of excess demand being met by coal fired generation in the ERCOT system (Table 8). The higher mpgCO_2 in the PSIV scenario may be due to the fact that the daytime charging prevalent in the PSIV scenario increases demand during a time when natural gas generation is more likely to be the marginal unit.

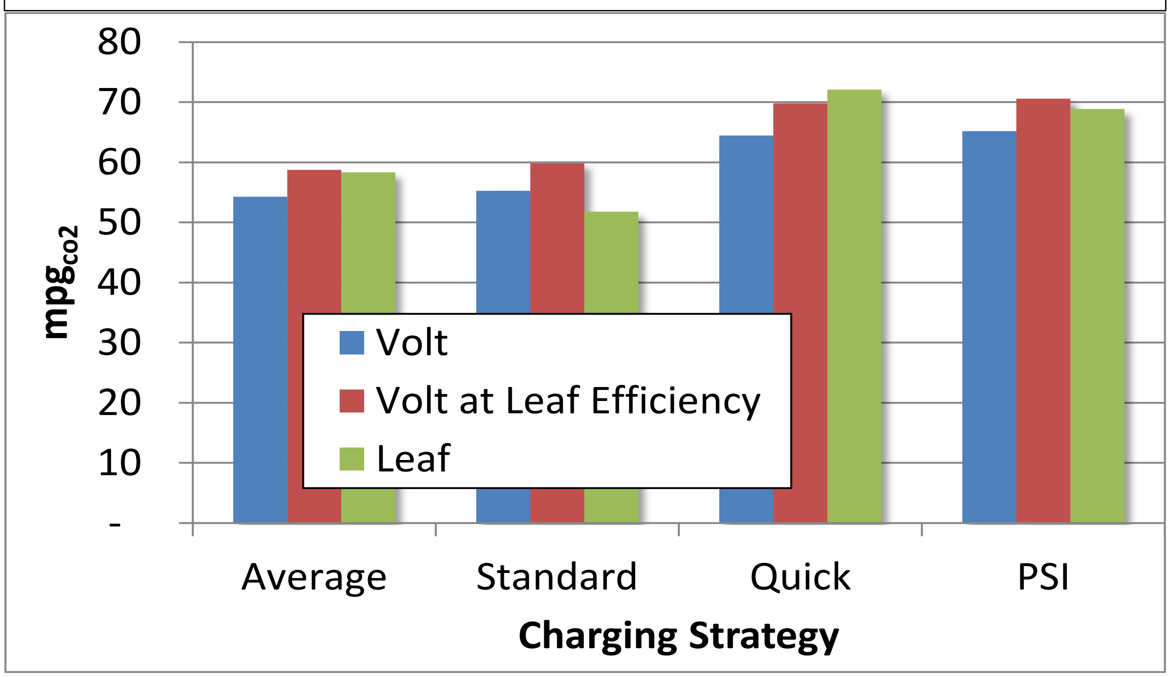
Table 8. MPG Equivalence by Charging Scenario and Pollutant

Sensitivity	mpg_{co2}	mpg_{noX}	mpg_{so2}
EVAV	54	36	0.4
EVSV	55	39	0.4
EVQV	64	49	1.1
EVPSI	65	44	1.1
EVAL	58	38	0.4
EVSL	52	38	0.4
EVQL	72	53	1.2
EVPSIL	69	48	0.9

Similarly, over 90% of the EV charging demand in the QL scenario is met through natural gas generation, making this sensitivity the highest mpgCO_2 of the sensitivities. Finally, the average and standard charging scenarios for both the Leaf and the Volt which have the highest proportion of coal used to meet EV charging demand 55% and 50% for average and standard charging respectively also have the lowest mpg_{co2} among the sensitivities.

This analysis provides useful insight into the differences between the manner in which differences in Volt and Leaf performance and charging profiles affect associated emissions. Vehicle efficiency appears to be the most significant factor in improving $mpgCO_2$, according to this analysis the Leaf achieves approximately 3.81 miles per kWh while the Volt achieves 3.52. If Volt efficiency were comparable to Leaf efficiency, $mpgCO_2$ for the Volt would increase by an average of 5 mpg (Chart 24). While there is some difference in mpg equivalence due to different charging needs of the two sample vehicles, efficiency appears to be the dominant factor, allowing the use of the Volt as a

Chart 24. Impact of Improved Volt Efficiency on $mpgCO_2$



rough proxy for electric vehicles in general in the sensitivities for the Load Leveling and Low Carbon Future Scenarios.

SO_2 emissions are clearly higher for EVs charging in ERCOT relative to ICEs, primarily as a result of the dramatically higher SO_2 emission rates for coal relative to the rest of the fleet, in particular for lignite facilities in Texas: Martin Lake, Monticello, and Big Brown. These facilities, totaling 8 of ERCOT's 35 coal powered generating units, account for over 50% of ERCOT's coal fleet generation. Compounding this issue is the fleet-wide coal SO_2 emission rate relative to ERCOT's system-wide SO_2 emission rate; in the case of CO_2 and NO_x, coal emissions are higher than other technology emissions by a factor of 1.6 and 1.04 respectively. The SO_2 emission rate for coal in ERCOT is almost 8 times as high as the system-wide average and 691 times higher than SO_2 emissions from combined cycle units. To demonstrate the impact of coal on mpgSO_2 an analysis of mpgSO_2 for the Base Case scenarios with the impact of coal generation removed is provided in Table 9, for illustrative purposes. The impact of EV charging on SO_2 emissions in ERCOT exceeds the impact of ICE use on a mile traveled basis, however the magnitude of increase in SO_2 output remains small in comparison to system-wide emissions, ranging from .05% - .34% of total system SO_2 emissions.

Table 9. MPG_{SO2} without coal plant impacts

Sensitivity	mpg_{so2}
EVAV	105
EVSV	119
EVQV	143
EVPSI	43
EVAL	124
EVSL	128
EVQL	155
EVPSIL	92

4.4.2) Load Leveling Scenarios – Reflecting the Impact of EV Charging Using the Current ERCOT Fleet Mix with Increased Energy Storage and Demand Response

The Load Leveling scenarios focus on Volt charging sensitivities to simplify this analysis, with non-EV and EV charging demand summed and then averaged over a rolling 12-hour period throughout the year. The LLBC scenario increases emissions slightly (by 0.3% for CO_2) when compared to the EVBC scenario as a result of a slight shift from natural gas to coal generation. Due to the nature of the notional load leveling used in this research the difference between scenarios is reduced significantly, resulting in a narrowing of the range of impacts on generation output from different charging strategies (Chart 25). This impact extends to the PSIV sensitivity where the differences in hourly charging patterns relative to other sensitivities are reduced slightly.

While the bulk power generation system emissions are increased in the Load

Chart 25: Change in Generation Output for a Representative Spring Day

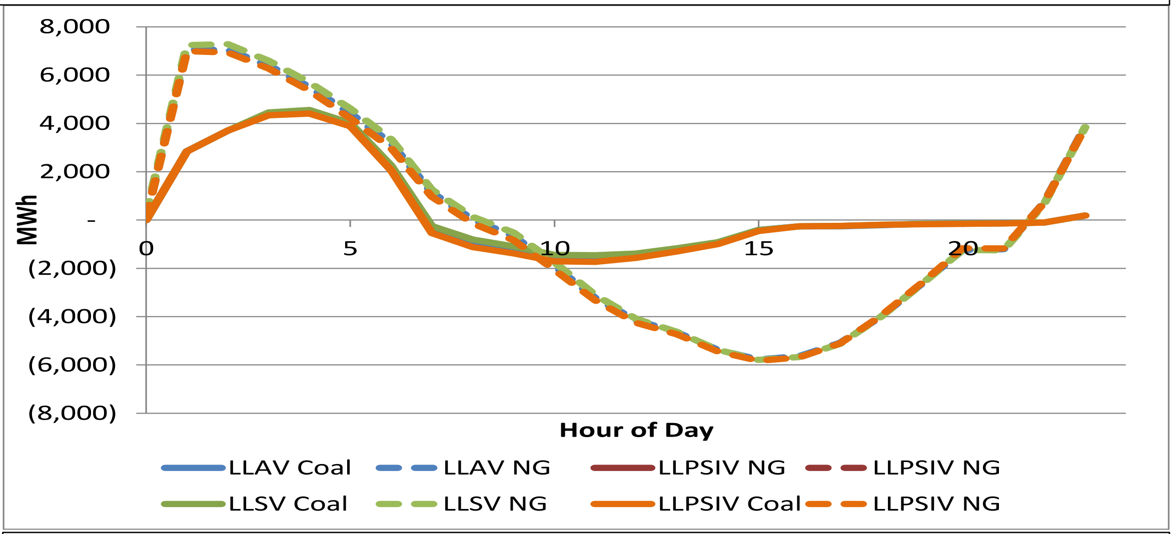


Chart 25 above shows the dramatic narrowing of differences in generation output for Load Leveling sensitivities, resulting in a reduction in differences of mpg equivalencies.

Leveling scenario and EV charging sensitivities, the impact of EV charging on system emissions is muted relative to the Base Case sensitivities. Coal generation is already higher in the LLBC scenario, and the bulk of the increase in generation output for most sensitivities comes from natural gas fired generation, with the result that the LL sensitivities have noticeably higher mpgCO_2 values. The effect for mpg NO_x is somewhat mixed as many single-cycle natural gas units in ERCOT do not control for NO_x emissions and in many cases have higher emission rates than the coal generation fleet (Table 10).

Table 10. Load Leveling Sensitivity MPG

Sensitivity	mpg_{co2}	mpg_{noX}	mpg_{so2}
LLAV	61	44	0.7
LLPSIV	65	46	1.4
LLQV	62	46	0.8
LLSV	61	45	0.7

4.4.3) Low Carbon Future Scenario – the Impact of Electric Grid Decarbonization on Equivalent MPG Measures for EVs

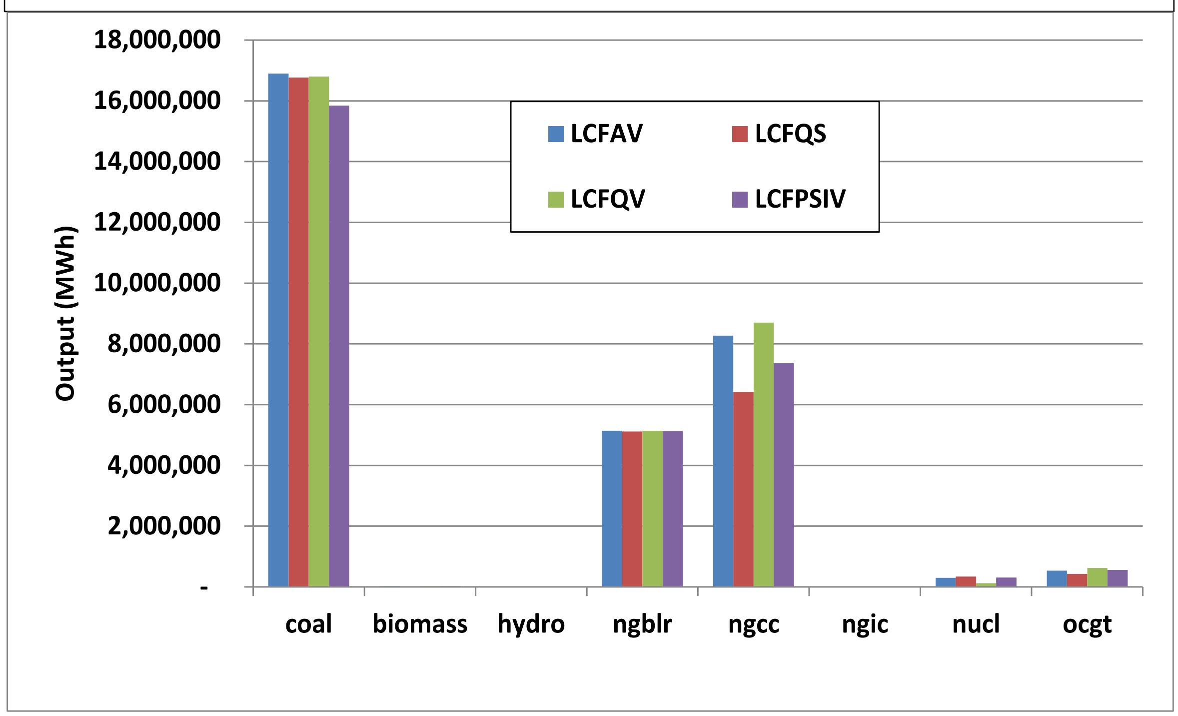
Results from the LCF set of scenarios are slightly counterintuitive when viewed in the context of mpg equivalence. Namely, under this scenario, coal units are more often the marginal unit, particularly during EV charging times. That means EV charging in a low-carbon scenario actually causes emissions to marginally increases. Since wind and solar energy have negligible marginal costs they are essentially price takers, resulting in the curtailment coal and even nuclear output in these scenarios. This analysis finds no conditions such as lack of load or other system constraints that limit the output of wind or solar generation at any hour. While some wind generation has been curtailed historically in ERCOT the completion of the CREZ transmission lines are expected to eliminate transmission constraints for the level of wind energy modeled in this analysis.

As a result of these factors, EV charging leads to additional marginal coal and natural gas output rather than any additional wind or solar output in these sensitivities (Chart 26) resulting in a lower mpg equivalence than the other scenarios (Table 11). The mpg equivalence analysis is important to understand the contemporary impact of vehicle switching under a given scenario; however it is important to recognize both the immediate and longer term impacts of EV switching on the bulk electric system. While EV charging is unlikely to marginally increase solar or wind output during the day or hour in which the charging occurs, it is possible that charging patterns may impact wholesale market prices in a manner that will incent new generation. This is especially relevant in the case of night-time wind generation: in general off-peak

Table 11. Low Carbon Future Scenario

Sensitivity	mpg_{co2}	mpg_{noX}	mpg_{so2}
LCFAV	43	24	0.2
LCFSV	50	25	0.2
LCFQV	45	25	0.2
LCFPSI	52	26	0.2

Chart 26: Electric Output Increase by Fuel Type



wholesale prices are low but increased EV charging may lead to higher prices during the night-time hours, providing an incentive to night-time generation which includes wind sited in west Texas. Finally it is important to consider the marginal impacts in the context of total emissions of the entire system this research examines, as discussed in the evaluation of the societal impacts of EV usage.

4.4.4) Post Hoc Adjustments and Interpreting Model Outputs

Model results discussed in this section are the product of successful PLEXOS simulations in which the simulation converged on an optimal solution for every day in the modeled year. In the Base Case scenario PLEXOS returned an infeasibility error for May 2 due to a single unit ramping constraint that remain unresolved as of the writing of this thesis. As a result, prior to running the Base Case scenario the loadshape was altered for May 2 to replicate April 27th, which was the same day of the prior week and closely followed the loadshape of May 2nd. The Base Case ran successfully and results do not seem unduly impacted by this adjustment.

Similarly, in the "Standard Volt" sensitivity of the "Load Leveling" scenarios, March 13 did not converge on a solution for reasons that remain unclear. To correct for this in the output from March 12 is used in the calculations which had a similar loadshape to March 13 and no other notable differences from the 12th. Finally, the fuel consumption output for several natural gas combined cycle plants are calculated incorrectly within the model, overestimating actual fuel consumption for a given level of hourly electric generation. This output was adjusted using an exogenous linear heat rate formula (mmBTu/kWh) in order to more accurately reflect emissions using fuel consumption-based emission rates. This error in the model did not seem to negatively impact the output of the affected units, however additional work is needed to improve the accuracy of the model. All other facility fuel consumption data is calculated using a polynomial formula to better reflect facility minimum and ramping consumption levels. As the output from these facilities generally reflect less than 1% of total system output, this change is unlikely to significantly impact the results.

4.4.5) Evaluating the Societal Impacts of EV Usage

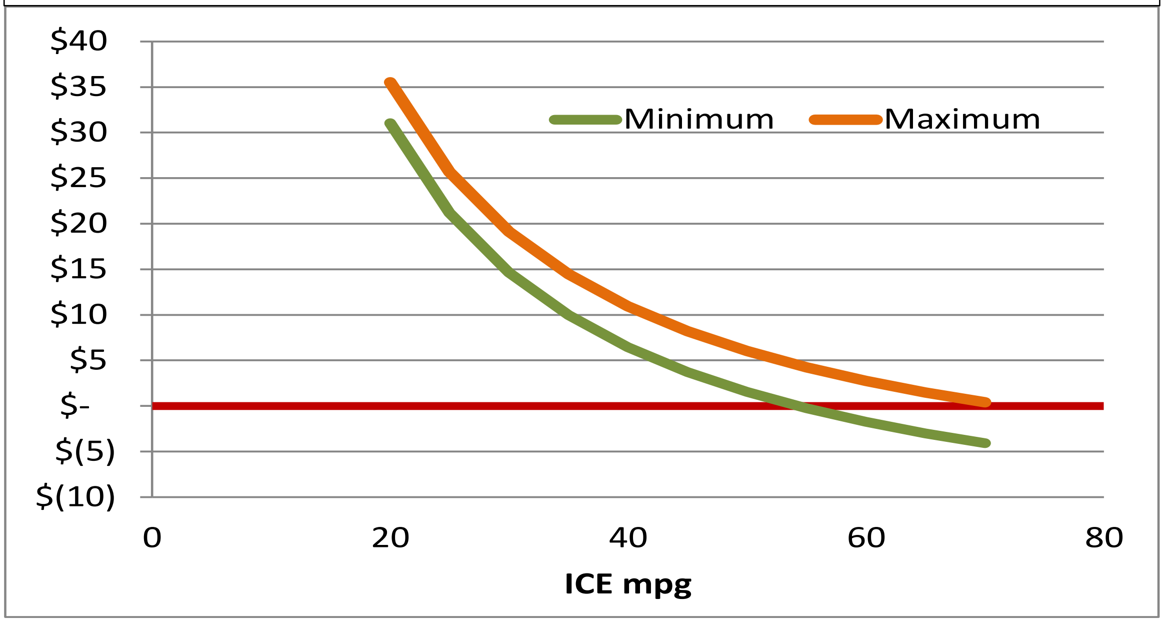
This section evaluates the modeling results in the context of societal benefit. The relative scale of impact for each pollutant discussed in the modeling review is important to understand, however it also is necessary to compare the overall emissions impact on equal terms to assess the full impact of the EV charging scenarios. These impacts are evaluated in an economic context, using U.S. allowance prices to value SO_2 and NO_x abatement (U.S. Energy Information Administration, 2012), including both 2011 and 2007 prices to estimate a range of impacts for those pollutants depending on market value. In 2007 SO_2 and NO_x prices reached an all-time high of $534/ton and $776/ton respectively, more recently prices have fallen dramatically with the low cost of natural gas and increased use of low-sulfur coal. Most recently available national data from the Energy Information shows 2011 allowance prices at $2/ton and $16/ton for SO_2 and NO_x respectively. As there is no national trading market for CO_2, this analysis uses the EPA's 2013 Social Cost of Carbon mid-range estimate for 2025 of $51/ton; the California cap-and-trade system's current price floor of ~$11/ton (Baker, 2013) is used to estimate a range of prices.

This approach draws a clear distinction between the scale of societal impacts of the levels of SO_2 and NO_x emissions relative to CO_2 emissions: even at the high range of SO_2 and NO_x prices and the low range of CO_2 prices, the impact of CO_2 reductions from EV charging overwhelms the impact the impact of SO_2 and NO_x increases in most cases (Chart 23). In performing the analysis selecting and efficiency level of the ICE used for comparison purposes is critical as it establishes the base level of annual emissions against which EV usage is viewed. This analysis assumes that all vehicles travel 10,000 miles annually and, for simplicity, that both the Leaf and Volt miles traveled are powered through electric charge (i.e. the Volt's ICE range extender is not considered in this analysis).

In all sensitivities, the societal benefits of reduced CO_2 emissions resulting from EV charging exceed the societal costs of increases in SO_2 and NO_x emissions based on both recent low and 2007 high allowance prices for those pollutants. Furthermore the impact of a high CO_2 valuation of \$51/ton outweighs the impact of high SO_2 and NO_x prices, driving societal benefits to between \$70 and \$90 per car annually in most cases, reducing the emissions of a 30 mpg ICE by 44%-58% depending on the vehicle and charging strategy.

These results can be viewed in the context of the ICE mpg assumed for comparative purposes to better understand how future fuel efficiency standards impact the societal benefit of EV vs. ICE usage. Chart 27 shows the impact of ICE mpg assumptions on the value of EV charging, with negative values toward the higher ICE efficiency range indicating that charging EVs with the current ERCOT generation fleet imposes a societal cost, assuming ICE efficiency more than twice today's average light-duty vehicle fleet efficiency. The minimum value for EV charging is taken from the lowest value charging strategy – EVAV – and the highest from EVQL which provides the greatest value of the sensitivities analyzed in this research.

Chart 27. EV Usage Benefits Compared to ICE Efficiency (mpg)



4.5) Considering the Impacts to the Combined System

Thus far this analysis has focused primarily on the emissions tradeoffs associated with EV charging as opposed to ICE usage under a variety of scenarios. A critical question remains regarding the emissions impact to the combined system, i.e. the impacts of the combination of increased renewable generation and EV usage on the combined emissions of the bulk electric system and affected vehicles. In this final analysis the work understanding the secondary impacts of renewable energy generation is useful to model the full impacts to the system of renewable energy generation where a stand-alone simulation may not.

In order to provide a comprehensive analysis the combined social cost of CO_2, NO_x, and SO_2 emissions is estimated using the low range of costs outlined in this section. This analysis estimates social costs for the bulk power system, the secondary emissions impacts of renewable generation, and the use of ICE vehicles in base case scenarios. In order to evaluate the impact of replacing ICE vehicles a 1-for-1 relationship is assumed between the miles traveled using an EV based on the charge available and the miles traveled using an ICE vehicle. To compare across scenarios an assumption is made that each vehicle drives its maximum electric-powered distance every day of the year (38 miles for the Volt, 80 miles for the Leaf).

This is equivalent to each vehicle travelling approximately 14,000 – 29,000 miles annually; resulting from an assumption of maximum possible miles traveled using a daily charging routine. While this estimate far exceeds the average miles traveled per vehicle annually, this analysis is focused on a relative comparison between two vehicles assuming identical behavior so the question of annual miles travelled is not central to this analysis. Finally, as this analysis is set in the future the possibility of improved ICE efficiency in 2025 must be taken into account. In this analysis ICE efficiencies of 30 mpg and 54.5 mpg are used for comparative purposes to provide a low and high estimate of societal savings respectively, depending on the efficiency of the ICE being replaced.

Several key results emerge from this analysis (Charts 25 and 26): first, the social benefit of reducing emissions in the bulk power system through the increased use of renewable energy in the Low Carbon Future Scenarios appears to greatly outweigh the other impacts examined. Much of this may result from a question of relative scale: first the renewable energy installed in these scenarios represents almost 35% of the bulk power system capacity, while 350,000 light-duty vehicles represents only 2% of Texas' current fleet (Texas Department of Motor Vehicles, 2010). Second, according to the EPA the bulk power sector accounts for 1,828.5 Tg CO_2e emissions, while the light-duty vehicle fleet accounted for 1,061.6 Tg CO_2e in 2011 (EPA, 2013f). These two factors should be taken into account in assessing the relative impacts of EV usages and renewable energy usage.

Chart 28 Societal Cost (Benefit) of Combined Emissions Impacts vs. a 30 mpg ICE

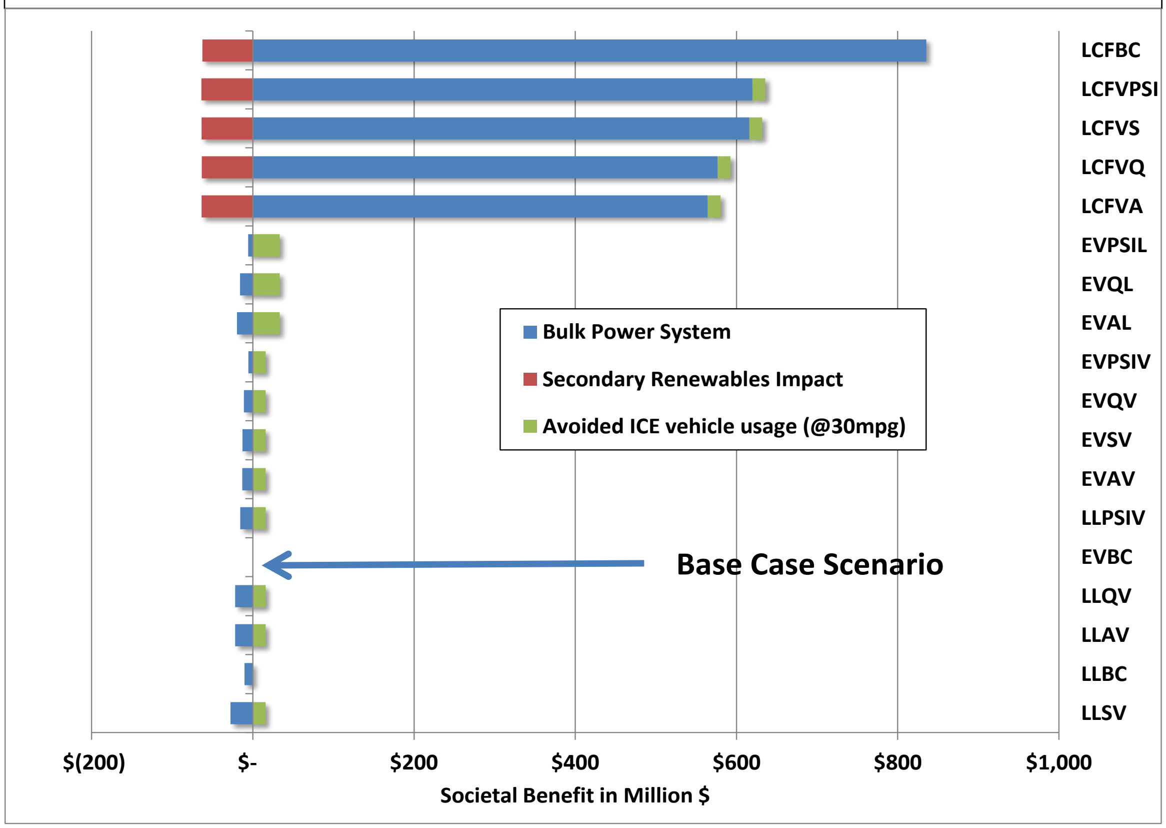
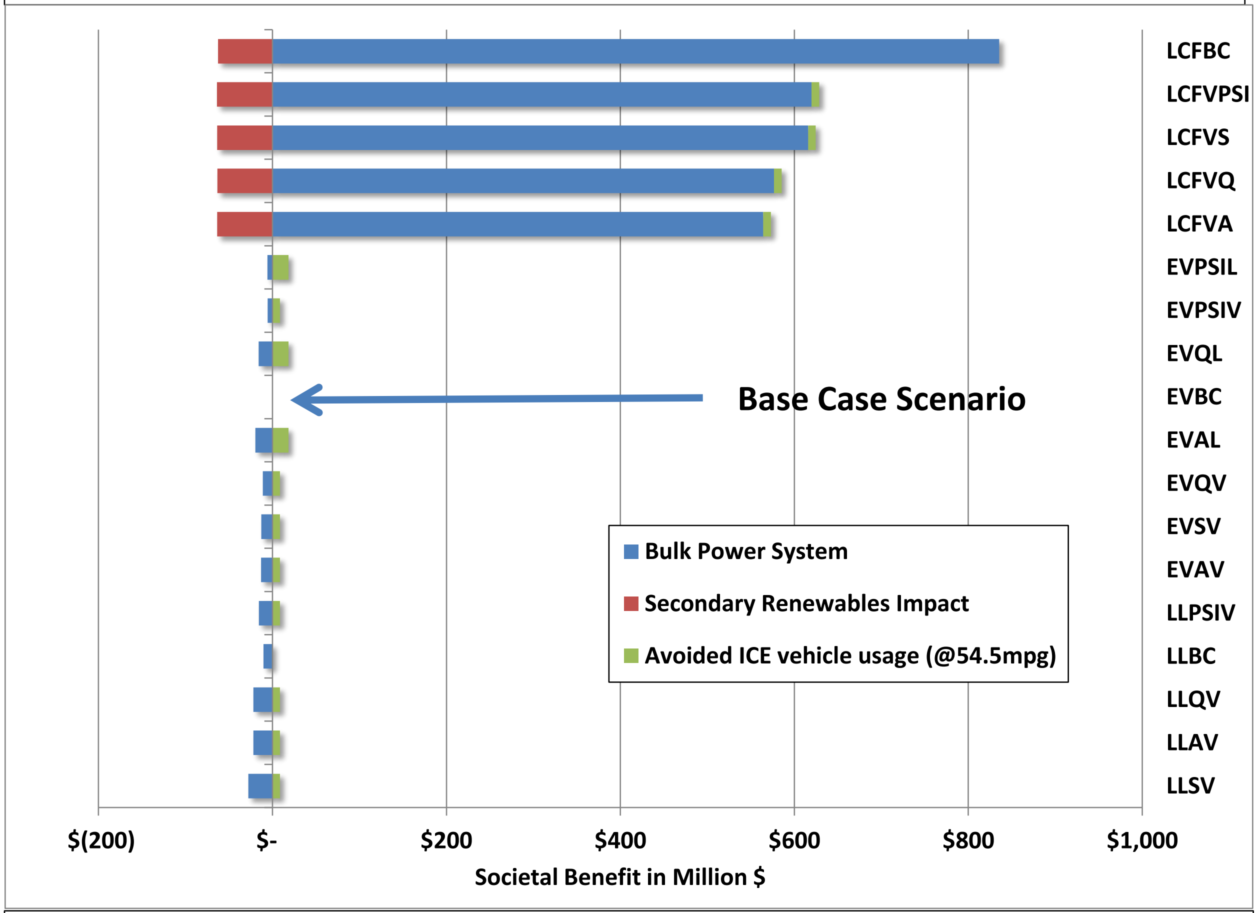


Chart 29: Societal Cost (Benefit) of Combined Emissions Impacts vs. a 54.5 mpg ICE



Charts 28 and 29 above show the social cost of different EV charging and bulk electric system scenarios relative to the base case scenario, assuming different efficiency levels for an ICE vehicle. Green represents savings from avoided ICE usage, while blue represents the impact to the bulk power system of EV charging and red is the secondary impact of increased renewable energy output. The line represents the total net cost: for a 30 mpg ICE most sensitivities have a lower social cost than the base case; for a 54.5 mpg ICE slightly less than half of the sensitivities reduce social costs relative to the base case. Scenarios with higher penetration levels of renewable energy significantly reduce social costs

The combined analysis also demonstrates the importance of ICE efficiency in evaluating these questions: assuming the higher mpg of 54.5 shifts the cost of eight sensitivities and the LLBC scenario above the cost of the base case scenario. Assuming a lower efficiency of 30 mpg, while still relatively high by today's standards, adds an additional $10 million in social costs and results in only three Load Leveling non-base case scenarios having a higher social cost than the base case scenario. Finally, these results show different EV charging strategies affect the combined emissions outcome within a scenario: in the LCF scenario the quick charging approach adds almost $40 million in social costs as a result of increased coal and natural gas combustion, while still being well below the social cost of the base case scenario.

The results of this analysis show demonstrable societal benefit from the replacement of relatively low efficiency ICEs with electric vehicles when charged using the current ERCOT electric generation fleet. The benefit is less clear as ICE efficiency improves to the 55 mpg range, and as the impact of EV charging on non-GHG pollutants is examined. Although the impacts of increased SO_2 and NO_x as a result of EV charging are minimal in this analysis further inquiry is needed to determine whether those impacts are regionally concentrated or diffuse. Taken as a whole, however this approach finds the use of EVs to replace ICEs to be generally beneficial toward society, given current and expected ICE efficiency levels within the modeling time frame used in this research. Further, as the attainment of fleet-wide CAFE standards is expected to depend at least somewhat on the expanded use of electric vehicles, it is possible that by 2025 the efficiency of new ICE vehicles may still be below the 54.5mpg federal fuel efficiency standard.

This analysis finds that under the current fleet mix, EV charging strategy can have a significant impact on the mpg equivalent per pollutant, although the societal benefit remains positive relative to a 30mpg ICE vehicle. The expansion of either demand response or energy storage in the bulk power system reduce the importance of EV charging strategy while retaining much of the societal benefit found in EV usage. In the low carbon scenarios coal generation becomes the marginal unit, resulting in a lower mpg equivalent, although the total impact is still a reduction in combined emissions relative to the base case.

5) Conclusion

5.1) Summary of Key Findings

This research finds that on a system-wide level secondary emissions due to wind variability have a minimal impact on the total emission impact of wind generation. Reductions in emissions as a result of increased wind output are several orders of magnitude greater than the secondary increases in emissions resulting from fossil fuel ramping due to wind energy variability. The secondary effect is too small to be considered statistically significant (at least for the uncertainties with this work), however the lack of statistical significance may be due primarily to the difficulty in assessing the impacts of net load on system and individual EGU emission rates. Using both a granular calculation of emission rates and incorporating the secondary effect of wind, our model indicates that wind reduced emissions in ERCOT from 2008 through 2011 by 7.4% for CO_2, 6.8% for NO_x, and 7.0% for SO_2.

Results for the PLEXOS simulation scenarios and sensitivities demonstrate that certain charging strategies significantly improve the vehicles mpg equivalence across pollutants, they also demonstrate that emission reductions from EV usage are possible for CO_2 and NO_x using today's electric generation infrastructure in Texas. While SO_2 emissions likely increase as a result of EV charging, the societal benefit of reduced NO_x

and CO_2 emissions is several orders of magnitude greater than the social cost of the slight increase in SO_2 emissions our results indicate. The results also indicate that future market conditions such as increases in low carbon generation, energy storage, and demand response play a significant role in the mpg equivalence for EVs.

The results of this analysis show demonstrable societal benefit from the substitution of EVs charged using the current ERCOT electric generation fleet for relatively low efficiency ICEs. The benefit is less certain as ICE efficiency improves to the 55 mpg range, and as the impact of EV charging on non-GHG pollutants is examined. Although the impacts of increased SO_2 and NO_x as a result of EV charging are minimal in this analysis further inquiry is needed to determine whether those impacts are regionally concentrated or diffuse. Taken as a whole, however this approach finds the use of EVs to replace ICEs to be generally beneficial toward society, given current and expected ICE efficiency levels within the modeling time frame used in this research. Further, as the attainment of fleet-wide CAFE standards is expected to depend at least somewhat on the expanded use of electric vehicles, it is possible that by 2025 the efficiency of new ICE vehicles may still be below the 54.5mpg federal fuel efficiency standard.

Finally, the combined impact of all pollutants resulting from bulk power system mix, EV charging and secondary emissions resulting from increased renewable energy output is estimated in the context of social costs. Through this approach both the EV charging strategy and ICE efficiency assumption can have a significant influence on the estimate of social cost; however both factors are of less significance than increased use of renewable energy in the bulk power grid. The significance of increased renewable energy use results in part from the penetration levels assumed relative to EV penetration levels, however current renewable penetration levels already exceed projected EV penetration levels.

5.2) Areas of Future Inquiry

This analysis contributes new findings to the literature regarding the emissions impacts of EV usage, at the same time it poses important questions for future inquiry, some of which can be addressed in the near term. As an example, this research can be extended to include economic effects on the bulk power system: changes in demand and renewable energy output are likely to affect wholesale power prices in ways that may alter the future mix of generation used to meet demand. Such an analysis might indicate whether EV charging has a noticeable effect on power prices, particularly during off-peak hours.

If that impact were to be verified it might provide an incentive for greater development of night-time generation such as West Texas wind. The PLEXOS software includes wholesale power price modeling, and although such an analysis is beyond the scope of this paper, preliminary results showing the hourly wholesale power price in each scenario and sensitivity are part of the output from the simulations run for this work. Going forward a useful first step would be to perform a straightforward analysis evaluating the differences in wholesale prices from each scenario on an hourly and seasonal basis.

This model may be used to further consider the confluence of a “load leveling” bulk power system with substantial additions of wind and solar power, as well as the possibility of even faster charging times. As discussed above the sub-regional impacts are important to consider as well: EVs reduce mobile point source emissions of ground level ozone precursors like NO_x and particulate matter. This may be of great benefit in urban areas struggling to comply with Clean Air Act regulations; often personal transportation emissions are a key hurdle to reducing emissions in non-attainment areas. At the same time the sub-regional impact of increased NO_x and SO_2 emissions should be further studied to determine whether those increases are significant within specific regions.

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